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DIVISION OF INFORMATION TRANSMISSION SYSTEMS AND MATERIAL TECHNOLOGY

Machine and Deep Learning Algorithms for Radio Resource Management in 5G and Beyond Networks

PhD Thesis

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ΕΘΝΙΚΟ ΜΕΤΣΟΒΙΟ ΠΟΛΥΤΕΧΝΕΙΟ
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Αλγόριθμοι Μηχανικής και Βαθιάς Μάθησης για Ανάθεση Ραδιοπόρων σε Δίκτυα 5ης και Επόμενης γενιάς

Διδακτορική Διατριβή

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Machine and Deep Learning Algorithms for Radio Resource Management in 5G and Beyond Networks

A Thesis submitted to attain the degree of
Doctor of Philosophy

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"Knowledge is so important
but imagination is more than that"

Albert Einstein

To my family…

Περίληψη

Τα τελευταία χρόνια, έχουν αναπτυχθεί συστήματα ασύρματων επικοινωνιών πέμπτης και επόμενης γενιάς (5G/B5G) για να υποστηρίξουν τον εκθετικό ρυθμό αύξησης της δικτυακής κίνησης και την πυκνή διασύνδεση των χρηστών, που απαιτεί αδιάλειπτη πρόσβαση στο μέσο. Η αυξανόμενη ανάγκη για νέους τύπους εφαρμογών (εφαρμογές Διαδικτύου των Πραγμάτων (IoT), επαυξημένη/εικονική πραγματικότητα (AR/VR), μη επανδρωμένα οχήματα (UAVs)) έχει οδηγήσει σε νέες κατηγορίες υπηρεσιών που εξυπηρετούνται από τα δίκτυα 5G/B5G. Έτσι, η υποστήριξη αξιόπιστης επικοινωνίας με χαμηλή καθυστέρηση (URLLC), η ενισχυμένη κινητή ευρυζωνικότητα (eMBB) και η μαζική επικοινωνία μηχανών (mMTC) σε περιβάλλοντα μαζικής πρόσβασης αποκτούν καίρια σημασία στα δίκτυα 5G/B5G. Επιπλέον, τα τελευταία χρόνια έχουν εισαχθεί καινοτόμες τεχνολογίες φυσικού επιπέδου για την αντιμετώπιση των αυξανόμενων προκλήσεων στον τομέα των ασύρματων επικοινωνιών, όπως τα κεραιοσυστήματα πολλαπλών εισόδων-πολλαπλών εξόδων (m-MIMO), οι χιλιοστομετρικές επικοινωνίες (mmWave), οι κόμβοι αναμετάδοσης (RNs), καθώς και η μη ορθογώνια πολλαπλή πρόσβαση (NOMA). Ωστόσο, οι προηγμένες αυτές τεχνολογίες φυσικού επιπέδου, όταν εφαρμόζονται σε ένα κυψελωτό περιβάλλον που χαρακτηρίζεται από υψηλά επίπεδα παρεμβολών και δυσχερείς συνθήκες διάδοσης, μπορούν να αυξήσουν το υπολογιστικό κόστος για την υποστήριξη των αυστηρών απαιτήσεων των χρηστών.

Σε αυτό το πλαίσιο, προτείνονται αλγόριθμοι μηχανικής μάθησης (Machine Learning - ML), ως ένας αποτελεσματικός τρόπος αντιμετώπισης των παραπάνω προβλημάτων, εξαιτίας της ικανότητάς τους να χρησιμοποιούν δεδομένα που παράγονται από το ίδιο το δίκτυο για τη βελτίωση της αποδοτικότητας του δικτύου. Οι αλγόριθμοι ML εκπαιδεύονται χρησιμοποιώντας, είτε δεδομένα που παράγονται από το ίδιο το ασύρματο δίκτυο, είτε από παρόμοια δίκτυα. Με αυτόν τον τρόπο, οι πολύπλοκοι υπολογισμοί για τα δεδομένα του καναλιού ενσωματώνονται στα επίπεδα των μοντέλων ML, γεγονός που οδηγεί στη μείωση του υπολογιστικού κόστους και της πολυπλοκότητας μετά από πολλαπλούς διαδοχικούς γύρους (rounds) εκπαίδευσης. Ορισμένοι αλγόριθμοι ML (π.χ. αλγόριθμοι ενισχυτικής μάθησης (Reinforcement Learning - RL)) μπορούν να αλληλεπιδρούν άμεσα σε πραγματικό χρόνο με το περιβάλλον και να υποστηρίζουν τις απαιτήσεις για χαμηλή καθυστέρηση σε δίκτυα 5G/B5G.

Αντικείμενο της παρούσας διδακτορικής διατριβής είναι η μελέτη και ανάπτυξη μεθόδων ML και Βαθιάς Μάθησης (Deep Learning – DL) για την αποτελεσματική ανάθεση ραδιοπόρων (Radio Resource Management – RRM) σε ασύρματα δίκτυα επικοινωνιών 5G/B5G. Συγκεκριμένα, μελετώνται ML/DL αλγόριθμοι για διάφορα RRM υποπροβλήματα, όπως η κατανομή υποφερόντων σε χρήστες (User Equipments – UEs), η επιλογή σταθμού βάσης (Base Station - BS) ή κόμβου αναμετάδοσης (Relay Node –RN) για χρήστες που εισέρχονται στην κυψελική τοπολογία, αλλά και η πρόβλεψη μετρικών δικτύου, όπως ο ρυθμός διέλευσης (throughput). Γενικά, οι αυξημένες απαιτήσεις των UEs για αδιάλειπτη ποιότητα υπηρεσίας (Quality of Service - QoS), ελαχιστοποιημένη καθυστέρηση και μεγάλη πυκνότητα διασυνδεδεμένων συσκευών, καθιστούν αναγκαία τη χρησιμοποίηση τεχνικών ML/DL για τα παραπάνω RRM προβλήματα. Μάλιστα, όταν στα 5G/B5G συστήματα γίνεται εκτενής χρήση προηγμένων τεχνολογιών φυσικού επιπέδου, όπως τα massive MIMO (m-MIMO) κεραιοσυστήματα, οι χιλιοστομετικές μπάντες συχνοτήτων (mmWaves) και η μη ορθογωνική πολλαπλή πρόσβαση διαίρεσης συχνότητας (non-orthogonal multiple access - NOMA), τότε η πολυπλοκότητα των RRM προβλημάτων και οι απαιτήσεις καθιστούν αναγκαίες ακόμη πιο εξελιγμένες ML τεχνικές. Για αυτόν το λόγο, πέραν των κλασσικών τεχνικών Επιβλεπόμενης (Supervised) και Μη-Επιβλεπόμενης (Unsupervised) μάθησης, η

παρούσα διδακτορική διατριβή μελετά και αναπτύσσει και τεχνικές Βαθιάς Ενισχυτικής Μάθησης (Deep Reinforcement Learning – DRL), και Deep Q-Learning αλγορίθμους. Στο ίδιο μήκος κύματος, μελετώνται και εφαρμόζονται στα παραπάνω RRM υποπροβλήματα και τεχνικές κατανεμημένης ML, όπως η Συνεργατική Μάθηση (Federated Learning – FL), όπου συνδυάζονται τα οφέλη της ML και του κινητού υπολογισμού (Mobile Edge Computing – MEC).

Αρχικά, στα πλαίσια της διατριβής, αναλύεται η υφιστάμενη κατάσταση, όσον αφορά στη ανάπτυξη ML αλγορίθμων για RRM προβλήματα για δίκτυα 5G/B5G, η σχετική βιβλιογραφία κατηγοριοποιείται με βάση το υπό μελέτη RRM πρόβλημα, αλλά και την εφαρμοζόμενη τεχνική ML.

Στη συνέχεια, αφού μοντελοποιηθεί μαθηματικά το RRM πρόβλημα σε δίκτυα 5G/B5G, τονίζεται η σημασία της πρόβλεψης των δικτυακών μετρικών (Key Performance Indicators - KPIs) για την αποδοτική επίλυση RRM προβλημάτων και πολλοί ML/DL αλγόριθμοι αναπτύσσονται και αξιολογούνται ως προς την απόδοσή τους στην πρόβλεψη του ρυθμού διέλευσης σε δίκτυα 5G/B5G.

Ένα ακόμα καίριο πρόβλημα σε 5G/B5G δίκτυα, όπου χρησιμοποιούνται Κόμβοι Αναμετάδοσης, είναι η βέλτιστη τοποθέτηση και επιλογή τους για κάθε χρήστη που εισέρχεται στην κυψελική τοπολογία. Επομένως, αφού μοντελοποιηθούν μαθηματικά και τα δύο αυτά προβλήματα (τοποθέτηση και επιλογή RN), μελετώνται ML/DL τεχνικές για την αποτελεσματική τους επίλυση. Για το πρόβλημα τοποθέτησης RN, προτείνονται δύο διαφορετικές DL προσεγγίσεις, οι οποίες εκπαιδεύονται και αξιολογούνται, βασιζόμενες σε σύνολα δεδομένων που παράχθηκαν από ένα MATLAB προσομοιωτή επιπέδου ζεύξης και συστήματος για 5G/B5G δίκτυα, όπου γίνεται εκτενής χρήση RN. Οι παραπάνω ML/DL αλγόριθμοι εκπαιδεύονται αρχικά σε ένα μόνο μηχάνημα, αλλά προτείνεται επίσης και ένα σχήμα Συνεργατικής Μάθησης για την κατανεμημένη εκπαίδευσή τους. Το σχήμα αυτό βασίζεται στη συνύπαρξη πολλών διασυνδεδεμένων συσκευών σε δίκτυα 5G/B5G, με αποτέλεσμα την αποφυγή υπερφόρτωση του δικτύου. Όσον αφορά στο πρόβλημα επιλογής RN, προτείνεται ένας καινοτόμος αλγόριθμος Βαθιάς Q-Learning μάθησης, που βασίζεται στην ταυτόχρονη μεγιστοποίηση της ενεργειακής αποδοτικότητας (Energy Efficiency - EE) και της φασματικής αποδοτικότητας (Spectral Efficiency - SE) για κάθε χρήστη της κυψελικής τοπολογίας. Επιπλέον, προτείνεται ένας συνολικός μηχανισμός για τη μεγιστοποίηση και της EE και της SE του συνολικού συστήματος.

Τέλος, οι παραπάνω προτεινόμενες λύσεις αξιολογούνται μέσω εκτενών προσομοιώσεων. Η αξιολόγησή τους περιλαμβάνει, επίσης, την μεταξύ τους συγκριτική αποτίμηση, αλλά και τη σύγκριση της απόδοσής τους έναντι άλλων προσεγγίσεων της πρόσφατης βιβλιογραφίας. Σε κάθε περίπτωση, οι ML προσεγγίσεις της παρούσας διατριβής επιτυγχάνουν σημαντικά κέρδη, όσον αφορά στα συνολικά επίπεδα EE και SE, και στην αξιοποίηση του διαθέσιμου φάσματος, ενώ λαμβάνεται υπόψιν και η υπολογιστική τους πολυπλοκότητα.

Λέξεις Κλειδιά: Δίκτυα 5^{ης} Γενιάς, Δίκτυα Επόμενης Γενιάς, Βαθιά Μάθηση, Μηχανική Μάθηση, Ανάθεση Ραδιοπόρων, Επικοινωνίες υποβοηθούμενες από Κόμβους Αναμετάδοσης, Q-Μάθηση, Ενισχυτική Μάθηση, Συνεργατική Μάθηση, Προσομοιώσεις Συστηματικού Επιπέδου, Κινητός Υπολογισμός στην Άκρη του Δικτύου.

Abstract

Fifth-generation (5G) and beyond (B5G) wireless communications systems have been established to support the exponential growth rate of mobile data traffic and dense user connectivity, which requires uninterrupted and location-free access to the medium. The emerging need for new application types (Internet of Things (IoT) applications, augmented/virtual reality (AR/VR), unmanned aerial vehicles (UAVs), etc.) has enabled telecommunication service categories served by 5G/B5G networks. In this context, the support of ultra-reliable low latency-communications (URLLC), enhanced mobile broadband (eMBB) and massive machine type communications (mMTC) in mass access environments is of utmost importance in 5G/B5G networks. Moreover, various novel physical layer technologies have been introduced over the last years to cope with the increasing challenges in the wireless communications domain, such as massive multi-input- multiple-output (m-MIMO) configurations, millimeter Wave (mmWave) transmission, Relay Nodes (RNs) as well as, non-orthogonal multiple access (NOMA). However, the aforementioned advanced physical layer technologies, when applied in a cellular environment characterized by high interference levels and complex channel approximations, can maximize the computational cost to support strict users' requirements.

Machine learning (ML) algorithms are proposed as an efficient way to tackle these considerations, due to their ability to utilize data generated by the network itself in improving network performance and efficiency. ML algorithms are trained using either data generated by the wireless network under test or by similar ones. In this way, complex channel calculations are encapsulated in ML models' layers, leading to a computational cost and complexity decrease, after multiple successful training rounds. Moreover, there are ML algorithms (e.g., Reinforcement Learning (RL) ones), which can directly interact in real-time and support low-latency requirements of modern era networks.

In the present thesis ML and Deep Learning (DL) methods are developed for efficient RRM in 5G/B5G wireless communication networks. More specifically, ML/DL algorithms are examined in various RRM subproblems, such as subcarrier allocation to active users (User Equipments - UEs), base station (BS) or RN placement and selection for users entering the cellular topology, as well as prediction of network key performance indicators (KPIs), such as throughput. The increased demands of the UEs for uninterrupted QoS, ultra-low latency and high density of connected devices necessitate the use of ML/DL techniques for the aforementioned RRM problems. Therefore, in addition to classical Supervised and Unsupervised learning techniques, this thesis explores Deep Reinforcement Learning (DRL) techniques, primarily Deep Q-Learning algorithms. Additionally, distributed ML techniques, such as Federated Learning (FL), are proposed for the aforementioned RRM subproblems, combining the benefits of ML and Mobile Edge Computing (MEC).

In the context of this thesis, a state-of-the-art analysis regarding ML-based RRM in 5G/B5G networks is firstly performed. The corresponding research works are categorized, based on both the RRM sub-problem, and the employed ML technique.

Then, the RRM problem in 5G/B5G networks is formulating and the significance of KPI prediction for RRM tasks is highlighted, while several ML/DL algorithms are developed concerning their performance in throughput prediction for 5G/B5G networks.

An additional key problem in 5G/B5G orientations, where RNs are deployed to extend each cell's coverage area and increase network's capacity, is the optimal RN placement and selection for each user entering the cellular topology. After formulating both problems (RN placement and selection) ML/DL frameworks are studied. Regarding the RN placement problem, two different DL approaches are developed and evaluated based on datasets created by a MATLAB RN-assisted 5G/B5G link and system level simulator. These ML algorithms

are not only deployed in a centralized manner, but also an FL framework is proposed. The coexistence of several interconnected devices in 5G/B5G networks, which can assist in splitting the computational overload among them, to efficiently utilize network resources. As far as the RN selection problem is concerned, a novel Deep Q-Learning scheme is proposed, based on the joint Energy Efficiency (EE) and Spectral Efficiency (SE) maximization for each user of the cellular topology. In addition, a specific mechanism is, also, implemented for the total system's EE and SE maximization.

Finally, all proposed solutions are thoroughly evaluated and tested via extended simulations. Comparisons are made, both among them and against other up-to-date approaches. In each case, significant performance gains are identified, leading to increased systems' EE and SE levels and important spectrum utilization, while the advantages of the proposed frameworks are, also, mirrored in terms of computational costs.

Keywords: 5G, B5G, Deep Learning, Machine Learning, Radio Resource Management, Relay Assisted Transmission, Reinforcement Learning, Q-Learning, Federated Learning, System Level Simulations, Mobile Edge Computing

Εκτεταμένη Περίληψη

Η ανάπτυξη δικτύων 5ης γενιάς (5G) επέφερε θεμελιώδεις αλλαγές στην αρχιτεκτονική, την υποδομή και τα λειτουργικά χαρακτηριστικά των ασύρματων δικτύων επικοινωνιών. Τα δίκτυα 5G έχουν αναπτυχθεί για να αντιμετωπίσουν τη μαζική συνδεσιμότητα και τις αυξημένες απαιτήσεις των χρηστών για αδιάλειπτες και διαφανείς επικοινωνίες χαμηλής καθυστέρησης, με την παράλληλη διατήρηση των επιθυμητών επιπέδων ποιότητας υπηρεσίας (Quality of Service – QoS) και ποιότητας εμπειρίας (Quality of Experience – QoE). Ωστόσο, νέες κατηγορίες εφαρμογών όπως οι επικοινωνίες οχημάτων (Vehicle-to-Vehicle communications), το διαδίκτυο των πραγμάτων (Internet of Things – IoT), η επαυξημένη και εικονική πραγματικότητα (AR/VR), οι ολογραφικές επικοινωνίες και η τηλεϊατρική, έχουν κάνει αισθητή την εμφάνισή τους απαιτώντας επικοινωνίες ακόμα μεγαλύτερου εύρους ζώνης, μηδενικής καθυστέρησης και εγγυημένων επιπέδων QoS, QoE με σχεδόν μηδενική μάλιστα πιθανότητα αποκοπής (99,99999% πιθανότητα εξυπηρέτησης). Για αυτούς τους λόγους, τα δίκτυα επόμενης γενιάς (Beyond 5G – B5G) βρίσκονται προ των πυλών, με ερευνητικές ομάδες τις 3GPP ήδη να εργάζονται πάνω στην προτυποποίησή τους με ορίζονται την έκδοση 19 (Release 19) των 3GPP τεχνικών προδιαγραφών.

Σε αυτό το πλαίσιο νέες τεχνολογίες φυσικού επιπέδου καλούνται να εφαρμοστούν σε 5G/B5G δίκτυα με στόχο την καλύτερη εξυπηρέτηση των μαζικών επιπέδων δικτυακής κίνησης και του ελέγχου της προκαλούμενης συμφόρησης. Τέτοιες τεχνολογίες, με καίρια σημασία σε 5G/B5G δίκτυα, είναι τα μαζικά κεραιοσυστήματα πολλαπλών εισόδων και πολλαπλών εξόδων (Massive Multiple-Input-Multiple-Output), οι κόμβοι αναμετάδοσης (Relay Nodes), η μη ορθογώνια πολλαπλή πρόσβαση (Non Orthogonal Multiple Access – NOMA) και άλλες.

Σε αυτό το περιβάλλον, η σημασία του καθορισμού αποτελεσματικών πολιτικών για την αποδοτική ανάθεση των διαθέσιμων ραδιοπόρων (Radio Resource Management – RRM) είναι τεράστιας σημασίας. Οι περιορισμένοι πόροι του δικτύου θα πρέπει να διατίθενται με έξυπνο τρόπο για να εξυπηρετούν τον αυξανόμενο αριθμό των ταυτόχρονα διασυνδεδεμένων συσκευών, την αυξημένη πυκνότητα των συνδέσεων αυτών, βελτιστοποιώντας ταυτόχρονα την χρήση του διαθέσιμου φάσματος και τη μείωση της συνολικής κατανάλωσης ενέργειας του συστήματος. Με άλλα λόγια, η ενεργειακή και η φασματική αποδοτικότητα (Energy Efficiency, Spectral Efficiency) αναδεικνύονται ως οι σημαντικότερες προς μεγιστοποίηση μετρικές δικτύου, σε σύγκριση με προηγούμενες γενιές δικτύων ασυρμάτων επικοινωνιών όπου η αξιολόγηση της απόδοσης των RRM πολιτικών που εφαρμόζονταν λάμβανε υπόψιν μόνο τη μεγιστοποίηση του ρυθμού διέλευσης. Ωστόσο, μια ακόμα σημαντική παράμετρος όπου θα πρέπει να λαμβάνεται υπόψιν κατά τη διαδικασία του RRM είναι η υπολογιστική πολυπλοκότητα (Computational Complexity) των προτεινόμενων RRM αλγορίθμων. Για την ακρίβεια σε δίκτυα 5G/B5G η συγκεκριμένη παράμετρος αποκτά ιδιαίτερη σημασία καθώς η συνύπαρξη προηγμένων τεχνικών φυσικού επιπέδου και πυκνών συνδέσεων, τείνει να αυξάνει εκθετικά τους χρόνους απόφασης.

Ως εκ τούτου, είναι κατανοητό ότι η επίτευξη της ιδανικής αναλογίας μεταξύ της βελτιστοποίησης των μετρικών δικτύου (EE, SE, ρυθμός διέλευσης) και της υπολογιστικής πολυπλοκότητας μπορεί να επιτευχθεί μόνο μέσω ενός αποτελεσματικού RRM μηχανισμού. Μέχρι τώρα, οι αποφάσεις RRM λαμβάνονταν ξεχωριστά για κάθε χρονοθυρίδα, με βάση τις τοπικές συνθήκες του δικτύου και τη συμφόρηση των συνδέσεων προς εξυπηρέτηση. Ωστόσο, οι αυξημένες απαιτήσεις των δικτύων 5G/B5G ενισχύουν την ανάγκη για ένα αποκεντρωμένο σύστημα που μπορεί να υποστηρίξει ευέλικτες αποφάσεις RRM. Προς αυτή την κατεύθυνση, η αξιοποίηση των δικτυακών δεδομένων μέσω της Μηχανικής Μάθησης (Machine Learning – ML) και η εξαγωγή χαρακτηριστικών μέσω των αντίστοιχων αλγορίθμων, μπορούν να συμβάλουν αποτελεσματικά στην βελτιστοποίηση των RRM πολιτικών που εφαρμόζονται.

Αντικείμενο της παρούσας διδακτορικής διατριβής είναι η ανάπτυξη και εφαρμογή μεθόδων Μηχανικής (Machine Learning – ML) και Βαθιάς Μάθησης (Deep Learning – DL) για την αποτελεσματική ανάθεση ραδιοπόρων (Radio Resource Management – RRM) σε ασύρματα δίκτυα επικοινωνιών 5G/B5G. Συγκεκριμένα, μελετώνται ML/DL αλγόριθμοι σε RRM υποπροβλήματα, όπως η κατανομή υποφερόντων σε χρήστες (User Equipments – UEs), η επιλογή σταθμού βάσης (Base Station - BS) ή κόμβου αναμετάδοσης (Relay Node –RN) για χρήστες που εισέρχονται στην τοπολογία, αλλά και η πρόβλεψη μετρικών δικτύου, όπως ο ρυθμός διέλευσης (throughput). Γενικά, οι αυξημένες απαιτήσεις των UEs για αδιάλειπτη ποιότητα υπηρεσίας (Quality of Service - QoS), ελάχιστη καθυστέρηση μετάδοσης και μεγάλη πυκνότητα διασυνδεδεμένων συσκευών, καθιστούν αναγκαία τη χρησιμοποίηση τεχνικών ML/DL για τα παραπάνω RRM προβλήματα. Επιπλέον, καθότι στα 5G/B5G συστήματα γίνεται εκτενής χρήση προηγμένων τεχνολογιών φυσικού επιπέδου, όπως τα massive MIMO (m-MIMO) κεραιοσυστήματα, οι χιλιοστομετρικές μπάντες συχνοτήτων (mmWaves) και η μη ορθογωνική πολλαπλή πρόσβαση διαίρεσης συχνότητας (non-orthogonal multiple access - NOMA), λόγω της πολυπλοκότητας των RRM προβλημάτων και των απαιτήσεων για άμεση απόκριση, απαιτούνται ακόμα πιο εξελιγμένες τεχνικές μηχανικής μάθησης. Η παρούσα διδακτορική διατριβή ασχολείται με τεχνικές Βαθιάς Ενισχυτικής Μάθησης (Deep Reinforcement Learning – DRL), και κυρίως με Deep Q-Learning αλγορίθμους. Επιπροσθέτως, μελετώνται και εφαρμόζονται στα παραπάνω RRM υποπροβλήματα και τεχνικές κατανεμημένης ML, όπως η Συνεργατική Μάθηση (Federated Learning – FL), όπου συνδυάζονται τα οφέλη της ML και του κινητού υπολογισμού (Mobile Edge Computing – MEC).

Η διάρθρωση της παρούσας διδακτορικής διατριβής παρουσιάζεται παρακάτω.

Στο *Κεφάλαιο 1* παρουσιάζεται η εξέλιξη των ασυρμάτων δικτύων επικοινωνιών, και δη των κυψελωτών, με έμφαση στα συστήματα 5G/B5G. Σε αυτό το πλαίσιο, παρουσιάζονται οι απαιτήσεις απόδοσης των δικτύων 5G/B5G, καθώς και οι τεχνολογίες φυσικού επιπέδου που υπόσχονται ακόμα μεγαλύτερα οφέλη όταν εφαρμοστούν σε τέτοια δίκτυα. Οι τεχνολογίες που αναλύονται περιλαμβάνουν τα m-MIMO συστήματα κεραιών, τα mmWaves, την NOMA, τα RNs και τις αναδιαμορφώσιμες έξυπνες επιφάνειες (Reconfigurable intelligent surfaces - RIS).

Στο *Κεφάλαιο 2* παρουσιάζονται οι βασικές αρχές και τεχνικές ML. Συγκεκριμένα, αναλύονται οι διάφοροι τύποι μάθησης με βάση την ύπαρξη ή μη ετικετών στα σύνολα δεδομένων (Επιβλεπόμενη, Μη-Επιβλεπόμενη, Ενισχυτική Μάθηση). Στη συνέχεια, το κεφάλαιο εστιάζει στις DL τεχνικές με έμφαση στην DRL και στην ανάλυση του αλγορίθμου Deep Q-Learning. Τέλος, παρουσιάζεται και το θεωρητικό υπόβαθρο της εφαρμογής κατανεμημένων ML τεχνικών, όπως η FL, σε 5G/B5G δίκτυα.

Στο *Κεφάλαιο 3* εξετάζεται η ανάγκη για ανάπτυξη ML μεθόδων για την επίλυση διαφόρων RRM προβλημάτων σε δίκτυα 5G/B5G. Πιο συγκεκριμένα, αρχικά, μοντελοποιείται το πρόβλημα της ανάθεσης ραδιοπόρων θέτοντας συγκεκριμένους στόχους βελτιστοποίησης και συγκεκριμένο σύνολο περιορισμών. Στην συνέχεια, παρουσιάζονται τεχνικές βελτιστοποίησης που δεν χρησιμοποιούν ML, και αναφέρονται τα μειονεκτήματά τους στο σύγχρονο περιβάλλον των 5G/B5G δικτύων. Επιπρόσθετα, παρουσιάζεται αναλυτική επισκόπηση της βιβλιογραφίας στο πεδίο της χρήσης ML για RRM προβλήματα και εξάγονται συμπεράσματα, αλλά και πιθανά προβλήματα στη διαδικασία ανάπτυξης και υλοποίησης ML μοντέλων για RRM προβλήματα.

Στο *Κεφάλαιο 4* επιλύεται η πρόβλεψη του ρυθμού διέλευσης, ως ένα ενδεικτικό πρόβλημα πρόβλεψης μετρικών σε ασύρματα δίκτυα νέας γενιάς. Αρχικά, αναλύεται η χρησιμότητα της a priori πρόβλεψης τέτοιων μετρικών για τη βελτιστοποίηση των στρατηγικών RRM. Στη συνέχεια, η απόδοση διαφόρων ML τεχνικών συγκρίνεται με βάση συγκεκριμένες ML μετρικές (key performance indicators - KPIs), όπως αυτά της ορθότητας (accuracy), της ακρίβειας (precision), της ανάκλησης ευαισθησίας (recall) και του f1-score. Τέλος, αναλύονται διεξοδικά τα συμπεράσματα της παραπάνω συγκριτικής αξιολόγησης.

Στο *Κεφάλαιο 5* μελετώνται αναλυτικά δυο καίρια RRM προβλήματα για 5G/B5G δίκτυα, τα οποία βασίζονται στη χρήση RNs για την ενίσχυση της ραδιοκάλυψης. Συγκεκριμένα, μελετάται η βελτιστοποίηση τόσο της τοποθέτησης όσο και της επιλογής RNs σε 5G/B5G δίκτυα. Αρχικά, μοντελοποιείται μαθηματικά το πρόβλημα της βέλτιστης τοποθέτησης RNs σε κάθε κυψέλη της 5G/B5G τοπολογίας. Στη συνέχεια, παρουσιάζονται και συγκρίνονται δυο DL αλγόριθμοι γι' αυτό το πρόβλημα, με χρήση συνόλων δεδομένων από έναν 5G/B5G προσομοιωτή δικτύου που αναπτύχθηκε στα πλαίσια της διατριβής. Μετά την αξιολόγηση των δύο παραπάνω αλγορίθμων, αναπτύσσεται και ένας κατανεμημένος FL αλγόριθμος που επιφέρει ακόμα μεγαλύτερη ακρίβεια τοποθέτησης RNs. Στο δεύτερο σκέλος του κεφαλαίου, μοντελοποιείται μαθηματικά το πρόβλημα της επιλογής RN για κάθε χρήστη που εισέρχεται στην τοπολογία. Στο πλαίσιο αυτό, αναπτύσσεται ένας DRL (Deep Q Learning) αλγόριθμος, ο οποίος μεγιστοποιεί τόσο την ενεργειακή και φασματική αποδοτικότητα (Energy Efficiency – EE και Spectral Efficiency – EE) κάθε περιοχής κάλυψης, όσο και τη συνολική EE και SE του συστήματος. Τέλος, παρουσιάζονται τα αποτελέσματα από την εφαρμογή του DRL αλγορίθμου, με βάση τη μεγιστοποίηση των παραπάνω μετρικών, και αναλύονται τα σχετικά συμπεράσματα.

Τέλος, στο *Κεφάλαιο 6*, συνοψίζεται η συνεισφορά της διατριβής, και προτείνονται θέματα και τεχνολογίες για μελλοντική έρευνα.

Στις παρακάτω ενότητες αναλύονται τα βασικά αποτελέσματα και οι προτάσεις που παρουσιάζονται τόσο στην παρούσα διδακτορική διατριβή, όσο και στις δημοσιεύσεις σε επιστημονικά περιοδικά και στα πρακτικά διεθνών συνεδρίων υπό κρίση.

1. Βιβλιογραφική Ανασκόπηση τεχνικών Μηχανικής Μάθησης για Ανάθεση Ραδιοπόρων σε 5G/B5G δίκτυα

Στο *Κεφάλαιο 3*, και συγκεκριμένα στην παράγραφο 3.1.2, παρουσιάζονται σημαντικές μέθοδοι βελτιστοποίησης για RRM προβλήματα σε δίκτυα 5G/B5G, οι οποίο δεν χρησιμοποιούν ML. Εστιάζοντας στα αποτελέσματα αυτών των ερευνητικών προσπαθειών, διαπιστώνονται αρκετοί περιορισμοί, που καθιστούν καίρια την χρήση ML σε RRM προβλήματα σε 5G/B5G δίκτυα. Συγκεκριμένα, στις περισσότερες περιπτώσεις LTE (Long Term Evolution) και πρώιμων 5G δικτύων η θέσπιση της πολιτικής RRM βασίζεται στην γνώση συγκεκριμένων παραμέτρων, όπως οι συνθήκες του καναλιού και της QoS για κάθε έναν από τους ενεργούς χρήστες του συστήματος. Ωστόσο, αυτό δεν είναι πάντα δυνατό σε 5G/B5G δίκτυα οδηγώντας σε υποβέλτιστες λύσεις. Τα μειονεκτήματα της χρησιμοποίησης τέτοιων τεχνικών RRM σε 5G/B5G δίκτυα είναι τα εξής:

- Οι περισσότερες από τις μη ML τεχνικές παρέχουν λύσεις που δεν είναι καθολικές. Οι παρεχόμενες λύσεις σχετίζονται σε μεγάλο βαθμό με την τοπολογία του δικτύου, τις απαιτήσεις και τα χαρακτηριστικά των χρηστών. Έτσι, το RRM, γενικά, είναι ένα πρόβλημα που χαρακτηρίζεται από μη συμβατικότητα.
- Οι παρεχόμενες λύσεις ενδέχεται να μην είναι διαθέσιμες σε πραγματικό χρόνο. Τα σύγχρονα δίκτυα ασυρμάτων επικοινωνιών έχουν υψηλά επίπεδα χρονικής μεταβλητότητας. Μια βέλτιστη λύση σε μια χρονική στιγμή δεν είναι εξ ορισμού βέλτιστη για την επόμενη.
- Το ασύρματο κανάλι διάδοσης σε δίκτυα 5G/B5G χαρακτηρίζεται από πολλαπλές παρεμβολές, και τυχαία μοντέλα κινητικότητας χρηστών. Σε αυτά τα σενάρια, η μαθηματική διατύπωση του προβλήματος είναι εξαιρετικά δύσκολη.

Για όλους αυτούς τους λόγους, πιο αποτελεσματικές RRM τεχνικές θα πρέπει να εφαρμόζονται λαμβάνοντας υπόψιν τόσο την υπολογιστική πολυπλοκότητα όσο και την αποδοτικότητα των δικτύων. Σε αυτό το πλαίσιο, προτείνονται στη βιβλιογραφία τεχνικές RRM που βασίζονται στην ML, ως ένας αποτελεσματικός τρόπος αντιμετώπισης των προαναφερθέντων περιορισμών.

Μετά τη συγκριτική μελέτη της βιβλιογραφίας σε σχέση με τη χρήση ML τεχνικών για RRM προβλήματα σε 5G/B5G δίκτυα, τα ακόλουθα συμπεράσματα μπορούν να εξαχθούν:

- Οι τεχνικές Επιβλεπόμενης Μάθησης (Supervised Learning) χρησιμοποιούνται κυρίως για προβλήματα πρόβλεψης δικτυακών μετρικών, όπως ο ρυθμός διέλευσης, ο λόγος σήματος προς παρεμβολή, οι απώλειες διαδρομής, κ.α.. Η πρόβλεψη τέτοιων μετρικών κρίνεται καίρια για την ανάπτυξη αποτελεσματικών RRM αλγορίθμων.
- Οι μέθοδοι Βαθιάς Μάθησης (Deep Learning – DL), λόγω της ικανότητάς τους να εξορύσσουν βαθιά δεδομένα και κρυμμένες συσχετίσεις ετικετών, μέσω πολλαπλών σύνθετων κρυφών επιπέδων, χρησιμοποιούνται κυρίως σε προβλήματα κατανομής υποφερόντων, επιλογής σταθμού βάσης (Base Station – BS) ή RN, κατανομής ισχύος και πρόβλεψης καναλιού. Η πολυπαραμετρική φύση του προβλήματος RRM και οι σύνθετοι συσχετισμοί χαρακτηριστικών του καναλιού καθιστούν τις προσεγγίσεις DL ως τον πιο αποτελεσματικό τρόπο αντιμετώπισης του συνολικού προβλήματος RRM.
- Από την άλλη πλευρά, η Μη Επιβλεπόμενη Μάθηση (Unsupervised Learning) εστιάζει, γενικά, σε προβλήματα ομαδοποίησης, όπως η ομαδοποίηση χρηστών, η επιλογή BS ή RN και η διαμόρφωση των επιπέδων QoS, όσον αφορά στο RRM.
- Τα μοντέλα Ενισχυτικής Μάθησης (Reinforcement Learning – RL) είναι πιο αποτελεσματικά στην αντιμετώπιση του συνολικού RRM προβλήματος, λόγω της ικανότητάς τους να αλληλοεπιδρούν με το περιβάλλον διάδοσης και να βελτιστοποιούν παραμέτρους όπως η EE και η SE, μέσω διαδοχικών γύρων εκπαίδευσης. Σε αυτό το πλαίσιο, RL τεχνικές, όπως η Q-learning, προτείνονται από ερευνητές σε προβλήματα κατανομής υποφερόντων και ελαχιστοποίησης κατανάλωσης ενέργειας.
- Τέλος, οι μέθοδοι Κινητού Υπολογισμού (Mobile Edge Computing – MEC) και Συνεργατικής Μάθησης (FL), προτείνονται για να αντιμετωπίσουν το δύσκολο ζήτημα της ελαχιστοποίησης του χρόνου εκπαίδευσης των ML μοντέλων και της βελτιστοποίησης της χρήσης των υπολογιστικών πόρων. Σε αυτό το πλαίσιο, οι μέθοδοι MEC και FL συνδυάζονται είτε με αλγόριθμους DL ή RL για διάφορα προβλήματα που σχετίζονται με το RRM, όπως η κατανομή χρηστών, η κατανομή υποφερόντων και η επιλογή BS ή RN. Επιπλέον, οι μέθοδοι FL μπορούν να συνδυαστούν αποτελεσματικά και με ανεπτυγμένες τεχνικές φυσικού επιπέδου, όπως η NOMA και οι Αναδιαμορφούμενες Έξυπνες Επιφάνειες (Reconfigurable Intelligent Surfaces – RIS) ώστε να ενισχυθούν περαιτέρω οι δυνατότητες των υπαρχόντων δικτύων, αλλά και να οδηγήσουν την μετάβαση προς την υλοποίηση δικτύων 6^{ης} γενιάς (6G).

2. Πρόβλεψη του ρυθμού διέλευσης σε 5G/B5G δίκτυα

Η πρόβλεψη δικτυακών μετρικών σε δίκτυα 5G/B5G είναι σημαντική για την αποτελεσματική διαχείριση των διαθέσιμων ραδιοπόρων και τη βελτιστοποίηση του δικτύου, καθώς μέσω της εξόρυξης γνώσης ενισχύεται σημαντικά η διαδικασία λήψης αποφάσεων που σχετίζονται με το RRM. Με την ακριβή πρόβλεψη των δικτυακών μετρικών, όπως ο ρυθμός διέλευσης, η καθυστέρηση, η ραδιοκάλυψη, η ισχύς του σήματος κ.α., επιτυγχάνεται βελτιστοποίηση των πόρων του δικτύου και αντιμετωπίζονται προληπτικά πιθανά προβλήματα, ενώ ταυτόχρονα μπορούν να βελτιωθούν τα προσφαιρόμενα επίπεδα QoS και QoE.

Σε αυτό το πλαίσιο, στο *Κεφάλαιο 4*, μελετήθηκε η πρόβλεψη του ρυθμού διέλευσης σε 5G/B5G δίκτυα. Χρησιμοποιήθηκε το σύνολο δεδομένων Lumos5G [158] που περιέχει παραμέτρους υλοποιημένων 5G δικτύων από τη Μινεσότα των ΗΠΑ. Τα χαρακτηριστικά του παραπάνω συνόλου δεδομένων περιλαμβάνουν παραμέτρους τοποθεσίας και κινητικότητας χρηστών (γεωγραφικό μήκος, γεωγραφικό πλάτος, ταχύτητα και κατεύθυνση, απόσταση χρήστη-BS και αντίστοιχες γωνίες), καθώς και δικτυακές παραμέτρους, όπως κατάσταση δικτύου (συνδεδεμένο ή μη), παραμέτρους καναλιού και ισχύος σήματος Ο μετρούμενος ρυθμός διέλευσης κατερχόμενης ζεύξης λειτουργεί ως η μεταβλητή απόκρισης.

Το παραπάνω πρόβλημα (πρόβλεψη του ρυθμού διέλευσης σε 5G/B5G δίκτυα) μελετήθηκε τόσο ως πρόβλημα ταξινόμησης (classification) όσο και ως πρόβλημα παλινδρόμησης (regression). Για αυτό το λόγο διάφοροι ML αλγόριθμοι χρησιμοποιήθηκαν και η απόδοσή τους αξιολογήθηκε με βάση ML μετρικές όπως η ορθότητα (accuracy) και το F1-Score για το πρόβλημα της ταξινόμησης, και το μέσο τετραγωνικό σφάλμα (Mean Squared Error - MSE) και το μέσο απόλυτο σφάλμα (Mean Absolute Error – MAE). Τα αποτελέσματα της παραπάνω ανάλυσης συνοψίζονται στον Πίνακα 1 (για πρόβλημα ταξινόμησης 2 ή 3 τάξεων) και στον Πίνακα 2 (για πρόβλημα παλινδρόμησης), και αναλύονται διεξοδικά στο *Κεφάλαιο 4*.

ML Αλγόριθμος	**3-τάξεις**		**2-τάξεις**		**Χρόνος Εκπαίδευσης**
	Accuracy	F1-score	Accuracy	F1-score	(s)
FFNN	0.81	0.67	0.88	0.88	960.41
k-NN	**0.87**	0.77	**0.90**	**0.90**	**111.79**
SVMs	0.76	0.53	0.82	0.82	150.03
DNN	0.81	**0.81**	0.85	0.84	129.43

Πίνακας 0-1: Αξιολόγηση ML αλγορίθμων για την πρόβλεψη του ρυθμού διέλευσης ως πρόβλημα ταξινόμησης

ML Algorithm	**MAE**	**RMSE**	**Χρόνος Εκπαίδευσης (s)**
Linear Regression	278	353	1.05
Binary Decision Tree	162	257	50.61
SVMs	278	354	28.54
NN	237	328	**6.89**
LSTM	**150**	**250**	276.89

Πίνακας 0-2: Αξιολόγηση ML αλγορίθμων για την πρόβλεψη του ρυθμού διέλευσης ως πρόβλημα παλινδρόμησης

Οι παραπάνω ML αλγόριθμοι συγκρίνονται και με άλλες προσεγγίσεις τις βιβλιογραφίας, όπου προκύπτει ότι η απόδοσή τους είναι ίδια ή και καλύτερη από την απόδοση αντίστοιχων μοντέλων.

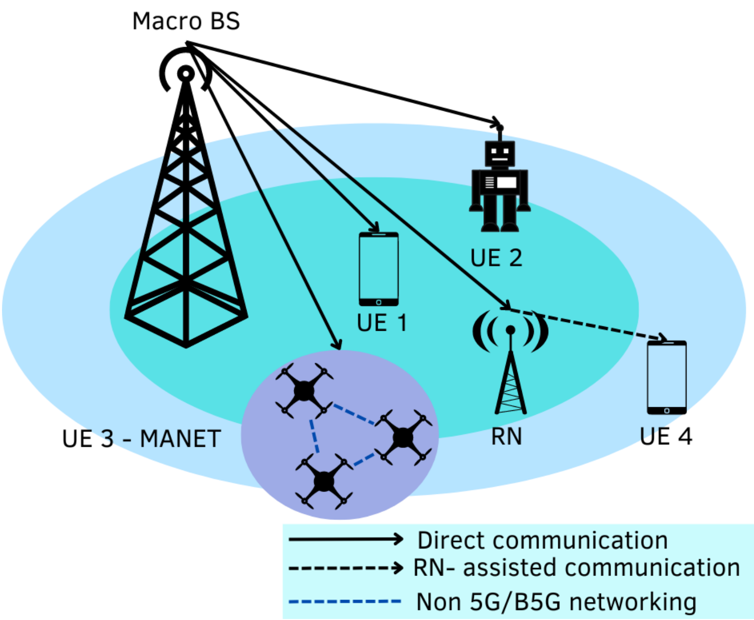
3. Τοποθέτηση και Επιλογή Κόμβων Αναμετάδοσης σε 5G/B5G δίκτυα μέσω Βαθιάς και Βαθιάς Ενισχυτικής Μάθησης

Στο *Κεφάλαιο 5* μελετάται το πρόβλημα της τοποθέτησης και επιλογής RN σε 5G/B5G δίκτυα με ανάπτυξη τεχνικών ML, με έμφαση στη Βαθιά και την Βαθιά Ενισχυτική μάθηση. Η χρήση RN είναι μία καινοτόμος τεχνική φυσικού επιπέδου οι οποία βρίσκει ιδιαίτερη εφαρμογή σε δίκτυα 5G/B5G, καθώς μπορεί να αυξήσει την χωρητικότητα της κάθε κυψέλης της τοπολογίας, αυξάνοντας το συνολικό αριθμό των αποδεχθέντων χρηστών σε αυτήν. Πέραν αυτού, η χρησιμοποίηση RNs είναι και ένας μη κοστοβόρος τρόπος αύξησης την περιοχής κάλυψης της κάθε κυψέλης, καθώς μπορούν να εξυπηρετηθούν απομακρυσμένοι χρήστες χωρίς την παράλληλη εγκατάσταση νέων σταθμών βάσης ή γενικότερα εξοπλισμού δικτύου ραδιοπρόσβασης. Λόγω των παραπάνω προτερημάτων των RNs, ή χρήση τους έχει κεντρίσει ιδιαίτερο ενδιαφέρον για εφαρμογές βελτιστοποίησης της παραγωγικής διαδικασίας, σε ιδιωτικά 5G/B5G δίκτυα αλλά και σε αμυντικά 5G συστήματα.

Σε *Κεφάλαιο 5*, αφότου παρουσιαστεί η παρούσα κατάσταση στη διεθνή βιβλιογραφία όσον αφορά τη χρήση ML τεχνικών για την βελτιστοποίηση της τοποθέτησης και επιλογής RN σε συστήματα 5G/B5G, παρουσιάζονται καινοτόμοι ML αλγόριθμοι για την αντιμετώπιση των παραπάνω προβλημάτων.

Συγκεκριμένα, θεωρώντας μια 5G/B5G τοπολογία (όπως αυτή της Εικόνας 0-1), υπάρχουν 2 τρόποι να εξυπηρετηθεί ένας χρήστης ο οποίος ζητά υπηρεσία. Αυτοί είναι:

- ***Το πρωτεύον σύστημα***, που αποτελείται από το σύνολο των BS, που αποτελούν τις οντότητες που παρέχουν πρόσβαση στους χρήστες και διαχειρίζονται τους πόρους του δικτύου.
- ***Το βοηθητικό σύστημα***, που αποτελείται από το σύνολο των RN. Αν ένας χρήστης δεν μπορεί να εξυπηρετηθεί από το πρωτεύον σύστημα για λόγους μεγάλων απωλειών διάδοσης (pathloss) ή για λόγους εξάντλησης των πόρων των BS, τότε ενεργοποιείται αυτό το σύστημα. Κάθε RN δρα συνεργατικά με τον BS στον οποίο «αναφέρεται».



Εικόνα 0-1: 5G/B5G επικοινωνίες με χρήση RN

Θεωρώντας λοιπόν ότι τι κυψελωτό σύστημα απαρτίζεται από M σταθμούς βάσης (BSs), R RNs and N ομοιόμορφα κατανεμημένους χρήστες, το πρόβλημα της βέλτιστης τοποθέτησης των RNs έγκειται στην επιλογή των N_{CRN} γεωγραφικών συντεταγμένων (x, y, z) για την τοποθέτηση αυτών των RN με βάση ένα πλήθος πιθανών συντεταγμένων RN_{can}, όπου $RN_{can} > N_{CRN}$. Η επιλογή αυτών των N_{CRN} RN γίνεται με βάση την ελαχιστοποίηση των απωλειών διάδοσης, την ελαχιστοποίηση της εκπεμπόμενης ισχύος για κάθε αποδεχθέντα χρήστη αλλά και την μεγιστοποίηση της χωρητικότητας κάθε κυψέλης.

Με τη χρήση ενός ημι-στατικού προσομοιωτή 5G/B5G επιπέδου ζεύξης και συστήματος, δημιουργούνται συνθετικά σύνολα δεδομένων για την εκπαίδευση DL αλγορίθμων με στόχο την επίλυση του παραπάνω προβλήματος.

Δύο διαφορετικές DL μέθοδοι προτείνονται για την επίλυση του παραπάνω προβλήματος, ενώ -και οι 2- αξιολογούνται στα ακόλουθα σενάρια:

- *Σενάριο 1*: Οι πληροφορίες του καναλιού θεωρούνται a priori γνωστές, και συγκεκριμένα ο πίνακας αποκρίσεων του καναλιού (channel coefficient matrix).
- *Σενάριο 2*: Δεν υπάρχει απολύτως καμία πληροφορία για τις συνθήκες του καναλιού.

Το δεύτερο μέρος αυτού του κεφαλαίου ασχολείται με το πρόβλημα της επιλογής του κατάλληλου RN (από τα N_{CRN} που εγκαταστάθηκαν με βάση το πρώτο υποπρόβλημα) σε δίκτυα 5G/B5G.

Η μαθηματική διατύπωση του παραπάνω προβλήματος βασίζεται στην ύπαρξη δύο διαφορετικών ζεύξεων που δρουν παράλληλα για την εξυπηρέτηση των χρηστών μέσω του βοηθητικού συστήματος. Η πρώτη είναι η ζεύξη μεταξύ του BS και του εκάστοτε RN, ενώ η δεύτερη είναι αυτή του RN με τον προς εξυπηρέτηση χρήστη. Συνεπώς, οι παράμετροι ενδιαφέροντος, δηλαδή οι παράμετροι με βάση την μεγιστοποίηση των οποίων γίνεται η επιλογή του κατάλληλου RN για κάθε χρήστη, υπολογίζονται μέσω της υπέρθεσης των παραμέτρων των δύο παραπάνω ανεξάρτητων ζεύξεων. Οι παράμετροι αυτοί είναι η ενεργειακή και φασματική αποδοτικότητα (EE, SE).

Για την επίλυση του προβλήματος της επιλογής RN παρουσιάζεται στο *Κεφάλαιο 5* ένα καινοτόμο σχήμα Βαθιάς Ενισχυτικής Μάθησης (DRL) που βασίζεται στον αλγόριθμο Q-Learning. Το προτεινόμενο DRL σχήμα αναλύεται διεξοδικά στην παράγραφο *5.4.2* ωστόσο τα βασικά του χαρακτηριστικά είναι τα ακόλουθα:

- Χρησιμοποιεί μια οντότητα που ονομάζεται πράκτορας λογισμικού (software agent) για την συνεχή αλληλεπίδραση με το κυψελωτό περιβάλλον.
- Ο αλγόριθμος δρα ανά κυψέλη και ανά χρήστη.
- Η αρχική κατάσταση του αλγορίθμου είναι η τυχαία επιλογή RN για τον εκάστοτε χρήστη.
- Σε κάθε επόμενο βήμα ο αλγόριθμος εξετάζει διαφορετικά διαθέσιμα RN για την εξυπηρέτηση αυτού του χρήστη, χρησιμοποιώντας των πίνακα συσχετίσεων του καναλιού, έως ότου βρεθεί το RN το οποίο βελτιστοποιεί την EE και την SE για τον υπό μελέτη χρήστη.
- Η σειρά των RN που θα εξεταστούν επιλέγεται με τη χρήση νευρωνικών δικτύων, διαφορετικών για κάθε κυψέλη.
- Στη συνέχεια, ενεργοποιείται ο μηχανισμός ελέγχου τη συνολικής EE και SE του συστήματος, ο οποίος είναι υπεύθυνος για την επίτευξη της ταυτόχρονης μεγιστοποίησης των επιπέδων EE και SE για το σύνολο της κυψελικής τοπολογίας.

Η αξιολόγηση της απόδοσης των παραπάνω προτεινόμενων αλγορίθμων για την τοποθέτηση και επιλογή RN σε 5G/B5G δίκτυα πραγματοποιήθηκε για ένα κυψελωτό σύστημα δύο (2) περιφερειών (tiers) κυψελών -και άρα δεκαεννέα (19) κυψελών- και είχε ως κύρια αποτελέσματα τα παρακάτω:

- Η προτεινόμενες DL μέθοδοι για την βελτιστοποίηση της τοποθέτησης των RN μπορούν να βελτιώσουν τη συνολική EE και τη αντίστοιχη SE του συστήματος έως και 30%, σε σύγκριση με πρόσφατους αλγορίθμους βελτιστοποίησης που δεν χρησιμοποιούν ML.
- Στο παραπάνω σύστημα, όταν ενεργοποιηθεί και το μοντέλο Βαθιάς Ενισχυτικής Μάθησης για την επιλογή RN, τότε η συνολική EE του συστήματος βελτιώνεται έως και 80% σε σχέση με την επίδοση του συστήματος που χρησιμοποιεί μόνο τον αλγόριθμο για την τοποθέτηση των RN. Η αντίστοιχη βελτίωση για την SE μπορεί να φτάσεις έως και το 75%.

- Η συνολική υπολογιστική πολυπλοκότητα και ο συνολικός χρόνος εκπαίδευσης βελτιώνεται αντιστοίχως σε σχέση με προσεγγίσεις που δεν χρησιμοποιούν ML.

4. Συμπεράσματα και Προεκτάσεις

Συνοψίζοντας, στην παρούσα διδακτορική διατριβή μελετήθηκε και αναλύθηκε διεξοδικά μία πληθώρα θεμάτων κατανομής ραδιοπόρων με ανάπτυξη αλγορίθμων μηχανικής μάθησης. Εντοπίζοντας τα κενά στην διαθέσιμη βιβλιογραφία και αξιοποιώντας σύγχρονες τεχνολογίες τηλεπικοινωνιών, και φυσικά πολλές διαφορετικές ML τεχνικές, στην τρέχουσα εργασία προτείνουμε ένα πλήρες και πρωτοποριακό πλαίσιο για την διαχείριση ραδιοπόρων και την βελτιστοποίηση της απόδοσης των ασύρματων δικτύων 5G/B5G. Βασικές κατευθύνσεις στην επίλυση των υπό εξέταση προβλημάτων αποτελούν η ενεργειακή αποδοτικότητα, η βελτίωση της ποιότητας υπηρεσίας, και η αύξηση της ικανοποίησης των αναγκών των χρηστών, προωθώντας έτσι ένα δεδομενοκεντρικό σύστημα για την ανάθεση των διαθέσιμων πεπερασμένων πόρων των δικτύων. Παράλληλα, έμφαση δίνεται στην χρησιμοποίηση RN, ως μια τεχνολογία αιχμής για την αύξηση της περιοχής κάλυψης σε 5G/B5G δίκτυα χωρίς ταυτόχρονη αύξηση του κόστους.

Ο αυξανόμενος αριθμός χρηστών, η απαίτηση για μαζική και άμεση συνδεσιμότητα, και η διάθεση πολλαπλών υπηρεσιών με υψηλές προδιαγραφές ως προς τον όγκο δεδομένων και οι νέες κατηγορίες εφαρμογών που θα διαδραματίσουν σημαντικό ρόλο στα B5G δίκτυα, αναδεικνύουν τους ML αλγορίθμους που παρουσιάζονται στην παρούσα διδακτορική διατριβή ως μία πολλά υποσχόμενη προσέγγιση τόσο για την διαχείριση των διαθέσιμων πόρων του δικτύου, όσο και για την ανάδειξη των RN ως μια τεχνολογία αιχμής με ορίζοντα την προτυποποίηση των δικτύων 6G.

Επιπλέον, οι προσομοιώσεις που διεξήχθησαν με την χρήση του ημι-στατικού MATLAB προσομοιωτή 5G/B5G επιπέδου ζεύξης και συστήματος αποδεικνύουν τα έμπρακτα οφέλη των προτάσεων της παρούσας διδακτορικής διατριβής ως προς την σημαντική βελτίωση των χαρακτηριστικών της λειτουργίας του δικτύου (πχ. ενεργειακή και φασματική αποδοτικότητα, αύξηση των ρυθμών μετάδοσης και των εξυπηρετούμενων χρηστών), αλλά και της υπολογιστικής πολυπλοκότητας, η οποία είναι καίριας σημασίας όσο οι υπολογιστικές διαδικασίες τείνουν να διαδραματίζονται στα άκρα του δικτύου.

Όσον αφορά στις μελλοντικές προεκτάσεις της παρούσας διδακτορικής διατριβής, κρίνεται πολύ σημαντική η εφαρμογή αντίστοιχων ML αλγορίθμων για προβλήματα RRM σε 6G δίκτυα όπου γίνεται επίσης χρήση νέων τεχνολογιών φυσικού επιπέδου για την κάλυψη των αναγκών των νέων κατηγοριών εφαρμογών προς εξυπηρέτηση. Το *Κεφάλαιο 6* παρουσιάζει και αναλύει συνοπτικά διάφορες τεχνολογίες που θα έχουν καίριο ρόλο στα 6G δίκτυα.

Τέλος, η παρούσα διδακτορική διατριβή διαθέτει όλα εκείνα τα χαρακτηριστικά τα οποία επιτρέπουν την προσαρμογή της για την επίλυση προβλημάτων διαχείρισης και κατανομής πόρων σε διαφορετικούς τομείς, όχι αποκλειστικά εντός του κλάδου των τηλεπικοινωνιών αλλά και σε άλλα πεδία στα οποία οι χρήστες αλληλοεπιδρούν και ανταλλάσσουν πληροφορίες. Ενδεικτικά, κάποιοι κλάδοι εφαρμογών όπου θα μπορούσε να γίνει χρήση παρόμοιων -φυσικά προσαρμοσμένων- ML προσεγγίσεων είναι τα δίκτυα μεταφορών, μετάδοσης ηλεκτρικής ενέργειας και η ιατρική μηχανική.

Glossary of Technical Terms – Γλωσσάρι Τεχνικών Όρων

5G Wireless Networks	Ασύρματα Δίκτυα 5ης Γενιάς
6G Wireless Networks	Ασύρματα Δίκτυα 6ης Γενιάς
Accuracy	Ορθότητα
Augmented Reality	Επαυξημένη Πραγματικότητα
B5G Wireless Networks	Ασύρματα Δίκτυα Επόμενης Γενιάς
Base Station	Σταθμός Βάσης
Classification	Ταξινόμηση
Computational Complexity	Υπολογιστική Πολυπλοκότητα
Dataset	Σύνολο Δεδομένων
Deep Learning	Βαθιά Μάθηση
Device-to-Device	Συσκευή-προς-Συσκευή
Downlink	Κατερχόμενη Ζεύξη
Energy Efficiency	Ενεργειακή Αποδοτικότητα
Federated Learning	Συνεργατική Μάθηση
Internet of Things	Διαδίκτυο των Πραγμάτων
Machine Learning	Μηχανική Μάθηση
Machine-to-machine	Μηχανή προς μηχανή
Mean Absolute Error	Μέσο Απόλυτο Σφάλμα
Mean Squared Error	Μέσο Τετραγωνικό Σφάλμα
Multiple-Input-Multiple-Output	Πολλαπλές-Είσοδοι-Πολλαπλές-Έξοδοι
Neural Network	Νευρωνικό Δίκτυο
Non Orthogonal Multiple Access	Μη-ορθογώνια τεχνική πολλαπλής πρόσβασης
Orthogonal Frequency Division Multiple Access	Ορθογώνια Διαίρεση Συχνότητας Πολλαπλής Πρόσβασης
Pathloss	Απώλειες Διάδοσης
Physical Layer	Φυσικό Επίπεδο
Quality of Experience	Ποιότητα Εμπειρίας
Quality of Service	Ποιότητα Υπηρεσίας
Radio Resource Management	Ανάθεση Ραδιοπόρων
Reconfigurable Intelligent Surfaces	Αναδιαμορφούμενες Έξυπνες Επιφάνειες
Regression	Παλινδρόμηση
Reinforcement Learning	Ενισχυτική Μάθηση
Relay Node	Κόμβος Αναμετάδοσης
Software Agent	Πράκτορας Λογισμικού
Spectral Efficiency	Φασματική Αποδοτικότητα
Supervised Learning	Επιβλεπόμενη Μάθηση
Test Set	Σύνολο Επαλήθευσης
Tiers	Περιφέρειες Κυψελών
Training Set	Σύνολο Εκπαίδευσης
Unsupervised Learning	Μη Επιβλεπόμενη Μάθηση
Uplink	Άνω ζεύξη
Vehicle-to-Vehicle Communications	Επικοινωνίες Οχημάτων
Virtual Reality	Εικονική Πραγματικότητα

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Giannis Bartsiokas,
16th of October 2023

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List of Acronyms

0G	Zero Generation
1G	1st Generation
2G	2nd Generation
3D	Three-dimensional
3G	3rd Generation
3GPP	Third Generation Partnership Project.
4G	4th Generation
5G	5th Generation
6G	6th Generation
A&F	Amplify-And-Forward
ABC	Artificial Bee Colony
AI	Artificial Intelligence
AM	Amplitude Modulation
ANN	Artificial Neural Networks
AP	Access Point
AR	Augmented Reality
B5G	Beyond 5th Generation
BBU	Baseband Processing Unit
BER	Bit Error Rate
BP	Blocking Probability
BS	Base Station
CAeC	Contextually Agile eMBB Communications
CD	Code Domain
CDMA	Code Division Multiple Access
CD-NOMA	Code Domain-NOMA
CF	Cell Free
CIR	Channel Impulse Response
CL	Centralized Learning
CN	Core Network
CNN	Convolutional Neural Network
COC	Computation Oriented Communications
CPU	Central Processing Unit
CRAN	Cloud RAN
CSI	Channel State Information
D&F	Decode-And-Forward
D2D	Device-to-Device
DL	Deep Learning
DL/UL	Down/Up Link
DNN	Deep Neural Networks
DQL	Deep Q-Learning
DRL	Deep Reinforcement Learning
EE	Energy Efficiency
eMBB	Enhanced Mobile Broadband
EMF	Electromagnetic Field
ETSI	European Telecommunications Standards Institute
FC	Femto-Cell
FEC	Forward Error Correction
FL	Federated Learning

FM	Frequency Modulation
FNN	Feed-Forward Neural Network
FR	Frequency Range
gNodeB	Next Generation Node B
H2H	Human-to-Human
HetNets	Heterogenous Networks
IMT	International Mobile Telecommunications
IoT	Internet of Things
IP	Internet Protocol
ITU	International Telecommunication Union
k-NN	*k*-Nearest Neighbors
KPI	Key Performance Indicator
L3	Layer 3
LOS	Line of Sight
LSTM	Long-Short Memory Network
LTE	Long Term Evolution.
M2M	Machine-to-Machine
MA	Margin Adaptive
MaC	Macro Cell
MANET	Mobile Ad Hoc Network
MAPE	Mean Absolute Percentage Error
MARL	Multi-Agent Reinforcement Learning
MC	Monte Carlo
MCTS	Monte Carlo Tree Search
MEC	Mobile Edge Computing
MIMO	Multiple-Input-Multiple-Output
MINLP	Mixed Integer Non-linear Programming
ML	Machine Learning
m-MIMO	Massive MIMO
mMTC	Massive Machine-Type Communications
mmWave	Millimeter Wave
MNOs	Mobile Network Operators
MOS	Mean Opinion Score
MRC	Maximal Ration Combining
MSE	Mean Squared Error
MTC	Machine Type Communications
MU-MIMO	Multi-User MIMO
NLP	Natural Language Processing
NOMA	Non-Orthogonal Multiple Access
non-IID	Non-Independent and Identical Distribution
NP	Non-Deterministic Polynomial-Time
NR	New Radio
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
OP	Outage Probability
O-RAN	Open Radio Access Network
OSI	Open Systems Interconnection
OTA	Over-the-Air
P2P	Point-to-Point
PA	Power Allocation

PD	Power Domain
PD-NOMA	Power Domain-NOMA
PF	Proportional Fairness
PHY	Physical Layer
PRB	Physical Resource Block
QoE	Quality of Experience
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RA	Rate Adaptive
RAN	Radio Access Network
RAT	Radio Access Technology
RB	Resource Block
ReLU	Rectified Linear Unit
RF	Radio Frequency
RIS	Reconfigurable Intelligent Surface
RL	Reinforcement Learning
RMSE	Root Mean Square Error
RN	Relay Node
RNN	Recurrent Neural Network
RRM	Radio Resource Management
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
RSSI	Received Signal Strength Indicator
SBA	Service-Based Architecture
SE	Spectral Efficiency
SER	Symbol Error Rate
SLA	Service Level Agreement
SNIR	Signal-To-Noise-Plus-Interference-Ratio
SNR	Signal-to-Noise-Ratio
SON	Self-Organizing Network
SU-MIMO	Single-User MIMO
SVM	Support Vector Machines
TD	Temporal Difference
TDMA	Time Division Multiple Access
UAV	Unmanned Aerial Vehicle
UE	User Equipment
UHF	Ultra High Frequency Band
URLLC	Ultra-Reliable-Low-Latency Communications
UxV	Unmanned ground, air, surface or undersea Vehicle
V2M	Vehicle-to-Machine
V2V	Vehicle-to-Vehicle
VR	Virtual Reality
WANET	Wireless Ad Hoc Network
WMMSE	Weighted Minimum Mean Squared Error
WSN	Wireless Sensor Network
WWWW	World-Wide-Wireless-Web

Preface

Within the framework of the present thesis, the utilization of novel Machine Learning (ML) algorithms has been studied as an effective tool to deal with various Radio Resource Management (RRM) problems in 5th generation (5G) and Beyond Networks (B5G). The proposed novel ML frameworks, spanned into different types of learning, are built and evaluated to deal with different RRM-related sub-problems, such as subcarrier allocation, Base Station (BS) or Relay Node (RN) placement and selection. A key observation is that different types of learning are witnessing the best-performance when applied to different RRM-related subproblems. As far as evaluation procedures, all the ML algorithms that have been deployed as part of this thesis, are evaluated in two phases regarding Key Performance Indicators (KPIs). These are:

- **ML KPIs**, where the maximization of metrics such as accuracy, f1-score, precision, recall, etc., is investigated. In fact, when having a dataset, the first level of evaluation of an implemented ML model considers, after splitting it on training and test sets, the performance of the aforementioned metric and the comparison of them with other recent approaches that can be found on the literature.
- **Network KPIs,** where metrics such as achieved throughput, total number of accepted users, Signal-to-noise-plus-interference-ratio (SNIR), energy efficiency (EE) and spectral efficiency (SE) are of interest. By evaluating the performance of the overall 5G/B5G systems', after the standalone evaluation of the ML KPIs, the effectiveness or not of the implemented ML algorithms is identified. In fact, if a ML method does not improves the performance of a 5G/B5G system, based on the evaluation of one or more of the aforementioned KPIs, then this method is declared as ineffective even though it's performance in the ML KPIs evaluation is satisfactory.

Concerning all the above, this thesis acts towards the direction of implementing an end-to-end data-driven ML framework so that different physical layer RRM tasks (e.g., KPI prediction, subcarrier allocation, RN placement and selection) can be optimized with, also, respect to the computational complexity degradation compared to existing non-ML optimization techniques.

Firstly, a comprehensive literature review is performed to list all the recent research efforts on the field of ML utilization for RRM-related problems in 5G/B5G networks. The analysis of the review is performed based on the type of learning (e.g. Supervised, Unsupervised, Reinforcement). By doing so, conclusions are reached as which ML types are suitable for the different RRM sub-problems.

Afterward, different ML frameworks are proposed for three main RRM sub-problems. These are the following:

- **KPI prediction**: In this case a comparative analysis of different ML models is performed focusing on Supervised and Deep Learning (DL) ones. Throughput is selected as the KPI of interest and evaluation is performed both concerning the achieved accuracy and f1-score of the implemented models, and the training time for each model. It is significant to note that the aforementioned models are evaluated not only using public datasets, but also, with datasets generated from the lab's MATLAB 5G/B5G networks' link and system level simulator.
- **RN placement**: As relaying is a key enabling technology in 5G/B5G, the optimal placement of RNs in each cell's coverage area is of high interest. For this purpose, using datasets generated from the lab's 5G/B5G network simulator, two different DL models have been designed and evaluated. The evaluation of this models concerns the comparison with state-of-the-art non-ML RN placement approaches.

However, due to the distributed nature of the 5G/B5G environment nowadays and the requirements for ultra-low latency communications, a Federated Learning (FL) framework for RN placement is, also, proposed and compared with the aforementioned centralized approaches.

- **RN selection**: Additively to RN placement, a key RRM problem in 5G/B5G networks is the selection of the best performing RN among the available ones to serve each user that cannot be served be the relevant BS. This RRM problems is declared as a really challenging one (categorized as NP-Hard problem), and, thus, traditional ML techniques cannot achieve good performance. For this purposed, a Deep Reinforcement Learning (RL) (Deep Q-learning) framework is proposed based on the maximization of both EE and SE both for the user under test, but also, additively for all the 5G/B5G system.

The rest of the thesis is organized as follows, as also depicted in Fig. 1:

1. Chapter 1 presents an overview on 5G/B5G cellular systems. The evolution of cellular systems through the years are briefly discussed in order to highlight the reason that led the research in 5G/B5 cellular system design. Moreover, the key performance and user requirements, which are extended compared to previous cellular networks generations, are presented according to 3GPP regulations. To finish with this chapter, the enabling physical layer technologies for 5G/B5G networks, which are also discussed and utilized throughout the whole thesis, are introduces. In this context, massive Multiple-Input-Multiple-Output (m-MIMO) antenna orientations, Non-Orthogonal Multiple Access (NOMA), RNs and 5G Sidelink and Reconfigurable Intelligent Surfaces are discussed. This chapter ends with the presentation of the 3GPP standardization activities plan toward 6^{th} generation (6G) networks establishment.
2. In Chapter 2, ML and DL principles are introduced, as well as the different types of ML. Afterwards, as the need for big datasets in different RRM tasks in 5G/B5G networks is growing, the focus is on DL. Moreover, distributed learning frameworks as FL and Mobile Edge Computing (MEC) are, also, introduced as the need for fast responses and ultra-low latency communications is critical in 5G/B5G communications.
3. Chapter 3 focuses on the effective ways that ML and DL can be used for the optimization of different RRM-related physical layer tasks in 5G/B5G networks. The RRM problem is formulated and traditional optimization techniques are presented. Afterwards, a detailed literature review of the state-of-the-art research works on the field of ML-enabled RRM is performed. Key outcomes, such as the dataset unavailability for these problems are, also, discussed. To tackle this challenges the last part of this chapter focuses on the implemented MATLAB link and system level 5G/B5G network simulator, which is hosted in Intelligent Communications and Broadband Networks Laboratory (ICBNet) premises at NTUA. This simulator is extensively used in this thesis for both dataset generation and models evaluation based on networks KPIs.
4. Chapter 4 focuses on the problem of KPI prediction in 5G/B5G network using ML/DL models. This thesis focuses on throughput prediction as an indicative case, due to the fact that this metric is one of the key ones when discussing performance of a cellular network. In this framework, different ML/DL algorithms are putted under test, and, thus, the results and the comparative analysis of the performance are discussed. Finally, outcomes and guidelines are retrieved.
5. Chapter 5 proposes the development of ML/DL/RL algorithms of the key RRM problems of RN placement and selection in 5G/B5G networks. Firstly, the relevant literature on the field is presented. Afterwards, two novel DL algorithms for

RN Placement are proposed and evaluated compared to existing non-ML approaches. However, due to the requirement for a flexible decentralized network with lots of different core network (CN) and Random Access Network (RAN) components in 5G/B5G, a decentralised FL framework is, also, proposed and evaluated for RN placement. Finally, the problem of RN selection is formulated and a novel deep RL (DLR), deep Q-learning, schemes is proposed and analysed, which focuse on the continuous optimization of both EE and SE.

6. Chapter 6 summarizes the conclusions and the contributions of the thesis and reflects on next steps and future research directions.

7. Appendix A presents the publications that are part of this thesis, as well as the reached citations from third parties until now.

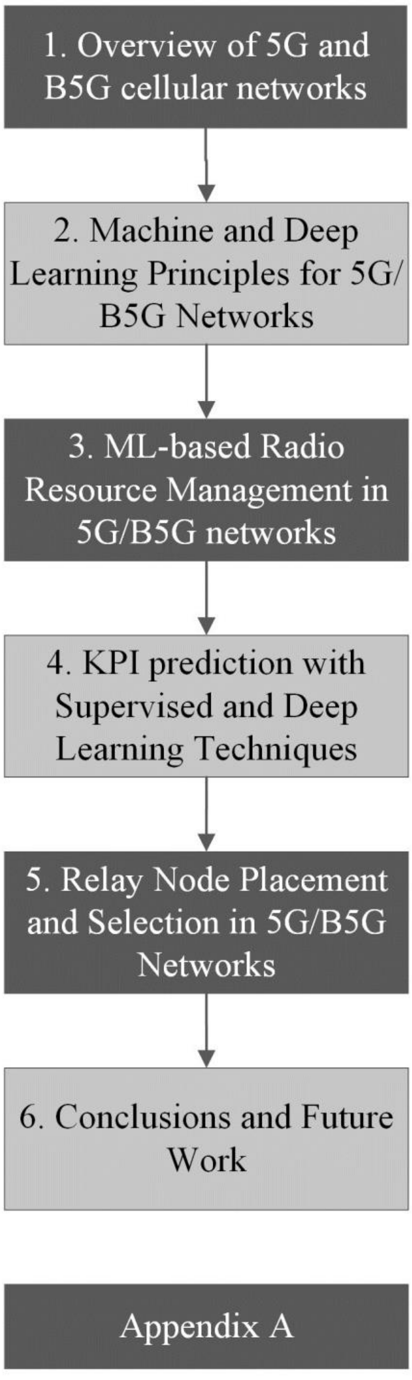


Figure 0-1: Thesis Overview

Chapter 1: Overview of 5G and B5G cellular networks

In this chapter the progress in the domain of cellular networks is introduced, focusing on 5G/B5G systems. In this framework, the user and performance requirements of 5G/B5G networks are discussed, as well as the enabling technologies that can support them. In paragraph 1.1 the evolution of wireless communication’s networks starting from the early wireless communication systems, till the forthcoming 6G ones. Paragraph 1.2 discusses the 5G/B5G network’s performance and user requirements. Paragraph 1.3 briefly introduces the technologies that are the key enablers of the 5G/B5G network’s advantages to support the aforementioned extended requirements. In this framework, m-MIMO antenna orientations, NOMA schemes, RNs and 5G sidelink and Reconfigurable Intelligent Surfaces (RIS) are discussed. Finally, paragraph 1.4 presents the 3GPP standardization activities towards the full deployment of 6G networks.

1.1 The Evolution of wireless communications networks (0G-6G)

The first globally used communication systems (excluding military systems, which are estimated to have been released earlier without clear evidence) were employed by 252 police departments in the United States and approximately 5,000 police vehicles in 1934 for public safety purposes. These systems utilized amplitude modulation. From the following year and the introduction of frequency modulation by Edwin Armstrong, all mobile communication systems are based on that technique. The precursor to cellular communication systems is the 0G (Zero Generation) technology. Its initial name was Mobile Radio Telephone, and it first appeared in 1946 in the United States as a collaboration between Motorola and Bell System. BSs were installed in 25 cities in the US, each with a coverage area of 50 km. The evolution of these networks included 0.5G networks and first-generation (1G) networks, which, despite continuous improvements compared to their predecessors, maintained analog signal processing in transceivers. A milestone for the development of cellular communication systems is the year 1979 when the first cellular system in Japan operated by Nippon Telephone and Telegraph. From that time onwards, there has been a vertical development in the aforementioned technologies, with a new generation of cellular systems being established approximately every 10 to 15 years. Thus, in 1988, the European Telecommunications Standards Institute (ETSI) designed GSM, the most significant second-generation network, which served 74% of the global mobile communication market until 2013. In the early 21st century, we entered the packet switching era with third-generation (3G) networks, which had been under research since 1980, and raised transmission rates to 2 Mbps, constituting 16% of the global market to date. After the full implementation of 3G, research began for the fourth generation (4G) of cellular systems. Its establishment began in March 2008 when the International Telecommunication Union-Radiocommunication Sector (ITU-R) defined a set of requirements for the 4G standards under the name IMT-Advanced. In contrast to previous generations, while the transition from 2G to 3G was as simple as changing SIM cards, mobile devices needed to be specifically designed to support 4G, as 4G does not support traditional circuit-switched telephony but rather IP-based communication, such as IP telephony. The pioneering technologies introduced by 4G are orthogonal frequency-division multiple access (OFDMA), frequency-domain equalization, and MIMO techniques. The aforementioned technologies, also, formed the basis of the fifth generation (5G) of (cellular) communication networks. Therefore, 5G pertains to the most advanced wireless network technologies. It utilizes millimeter-wave (mmWave) bands that offer performance of up to 20 gigabits per second and m-MIMO, which provides throughput levels up to ten times faster than 4G. It is of significant importance to note that in the aforementioned historical and conceptual approach, the development and implementation of new generations of networks are not static, and the new networks do not replace the old ones as isolated components. There is compatibility and direct dependence on previous and subsequent technologies. Thus, the terms evolution and compatibility are intertwined and form a unified whole for wireless communications. However, some more emphasis should be given 5G and 6^{th} generation (6G) networks and the technologies they employ, as they signify the domain of the present thesis.

In recent days, the ever increasing demands for increased data rates and the enormous volume of data traffic have highlighted the need for a new generation of mobile communication networks. This generation (5G), after several years of research and testing, has been deployed in the majority of the countries around the world. With the rapid growth of the Internet of Things (IoT), industry 4.0, augmented/virtual reality (AR/VR) applications, massive data volume is generated by end-user devices. In fact, according to CISCO [1], the monthly data demand will reach 100 exabytes with about 31.6 billion connected devices by 2023, thus doubling the current requirements. Moreover, IoT and connected car applications are expected to be the most growing application type. Fifth-generation networks (5G), which have been recently deployed around the world, support a wide range of trending applications by categorizing them in different usage scenarios. The ultimate goal is for 5G networks to operate based on the IPv6 protocol, providing unrestricted access to information and the ability to share data anywhere and by anyone with respect to Quality of Service (QoS), Quality of Experience (QoE), EE and SE requirements. Thus, an end-to-end wireless world, which supports the vision for a Worldwide Wireless Web (WWWW), can be fulfilled. Therefore, the primary objectives of 5G are to provide immense capacity and connectivity, and to deliver truly real-time multimedia applications instantly available across the globe. However, all of the above should be accompanied by the highest possible protection and quality of service (QoS). The key attributes of 5G networks are the following [2]:

- Less traffic, low cost, bidirectional bandwidth
- Global availability
- Software Defined Networking
- Connectivity up to 25Mbps
- More than 1GB bandwidth
- Supporting virtual private networking and Network Slicing
- Remote diagnostics
- Adaptive modulation techniques
- Artificial Intelligence (AI) and ML utilization

However, despite the numerous benefits of 5G networks, the large amount of generated data and the need for real-time responses by the network itself have raised the discussion in both industry and academia over a new generation of wireless networks, the 6G. The main goal of 6G networks, as described in [3], is to provide the relevant technologies that can transform the “connected things” world (as expressed by the 5G-related worldwide wireless web (WWWW) and the service-based architecture (SBA) model) into the “connected intelligence” world by implementing data-aided models for diverse tasks, applications, and Open Systems Interconnection (OSI) levels.

It is already visible that to achieve the aforementioned revolution, user requirements should be even stricter than the current 5G ones. As depicted in both [3] and [4], these extended requirements are expected to be the following:

- Increased data rates around 1 Tbps.
- EE as the primary KPI to support dense connections and mass connectivity for energy/battery-saving IoT devices and Unmanned ground, air, surface or undersea Vehicles (UxVs).
- Enhanced low latency which is translated in less than 1ms end-to-end latency.
- Upper mmWave communication bands and Terahertz bands (e.g., 73GHz-140GHz and 1THz-3THz).
- Increased coverage by minimizing the disconnection probability.
- End-to-end AI and ML capabilities.

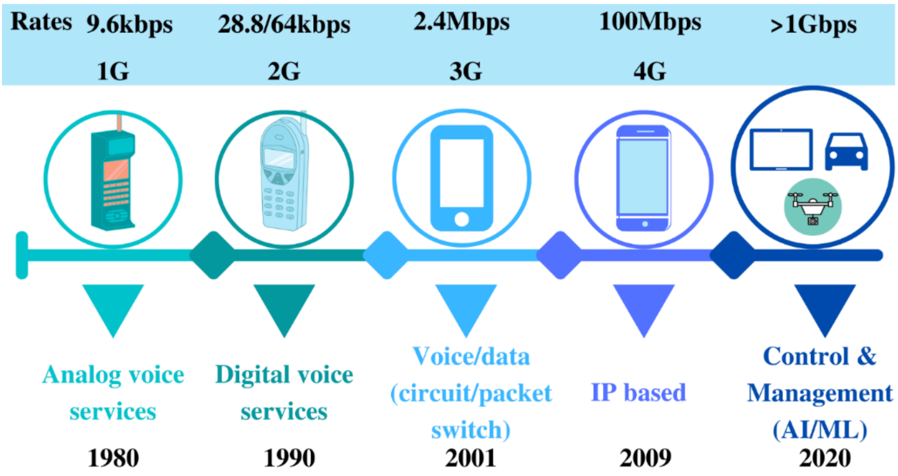
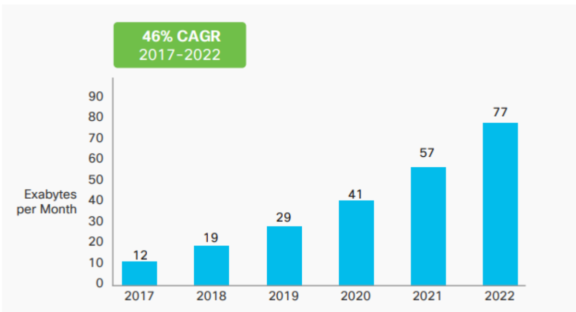
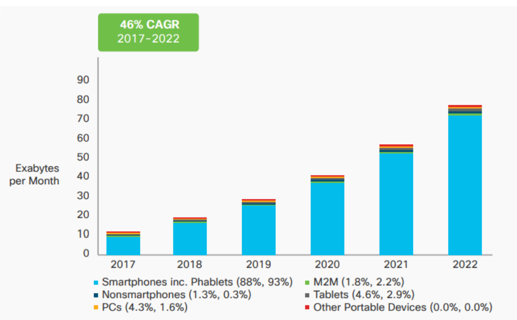


Figure 0-1: Wireless Communications Networks' evolution (1G-5G)

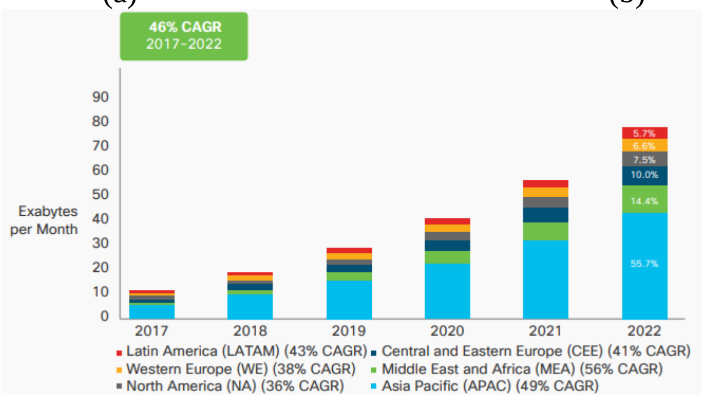
1.2 5G and 6G networks' Performance Requirements

The development of 5G wireless broadband networks has significantly accelerated in recent years and is globally in the stage of installation and network infrastructure deployment, with many mobile service providers already offering devices (such as mobile phones, tablets, chips, etc.) that support these specific networks. According to CISCO studies [2] (see Figure 1-2), monthly data demand is projected to reach 100 exabytes, with approximately 31.6 billion active devices by 2023, doubling the current requirements. In this context, the need for optimal solutions in network management and distribution of available radio resources becomes evident.





(a) (b)



(c)

Figure 0-2: Data traffic prediction 2018-2023[2] (a) Overall, (b) per device type, (c) per location

It is evident, therefore, that 5G ensures and enhances the availability of existing and new demanding applications and services, such as vehicle-to-vehicle (V2V) communications, device-to-device (D2D) communications, machine-to-machine (M2M) communications, and the Internet of Things (IoT). According to the International Telecommunications Union (ITU) (see Figure 1-3), the performance requirements of 5G networks are categorized as follows:

- Enhanced Mobile Broadband (eMBB): High-speed wireless communication for broadcast-like services (ITU MIT-2020 specification) Applications: HD videos, AR/VR applications, 3D online gaming
- Ultra-Reliable Low-Latency Communications (URLLC): Extremely reliable and low-latency communications Applications: Critical scenarios (telemedicine, natural disasters), V2V, M2M, autonomous networks (robotics applications)
- Machine-to-Machine (M2M) communications Applications: Increased connectivity of IoT devices and the development of corresponding networks and applications

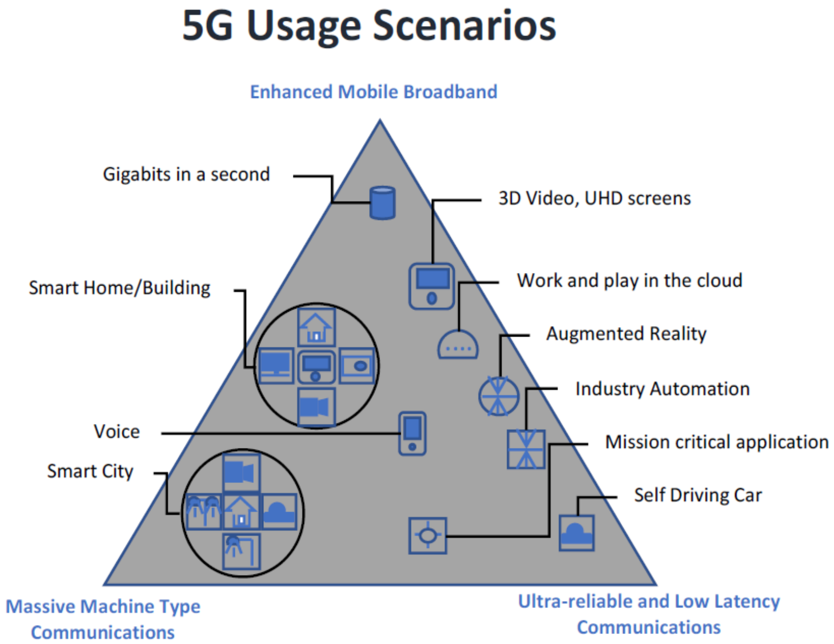


Figure 0-3: Performance Requirements and 5G usage scenarios, Source: ITU

Thus, 5G networks are required to adequately meet the aforementioned requirements, which can be summarized in terms of network metrics as high throughput and connection density in environments with high terminal device mobility, subject to the maintenance or even improvement of the high levels of QoS and QoE for the served users (see also Table 1-1).

Use cases	Requirements	Desired value(s)
Autonomous Vehicle Control	Latency/availability/reliability	5 ms/99.999%/99.999%
Emergency communication	Availability/energy efficiency	99.999%/1 week battery life
Factory automation	Latency/reliability	1 ms/>10-9 packet loss
High-speed train	Traffic density/throughput/mobility/latency	DL 100Gbps/km2/50 Mbps/and UL

		50Gbps/km2/100 Mbps/ 500 kmph/10 ms
Large outdoor event	Throughput/density/reliability	300 Mbps/4 devices/ km2/Out. Prob. < 1%
Massive user terminals	Density/availability/energy efficiency	1M devices/km2/99.9%/10-year battery life
Media on demand	Throughput/latency/density/availability	15 Mbps/ 200 ms/4000 devices/ km2/95% coverage
Remote surgery	Latency/reliability	1 ms/99.999%
Shopping mall	Throughput/availability/reliability	300Mbps (DL) 60Mbps (UL)/95%/95%
Smart city	Throughput/density	300Mbps (DL) 60Mbps (UL)/200000 devices/km2
Stadium	Throughput/density	0.3-20 Mbps/0.1-10 Mbps/km2
Smart grids	Latency/reliability	8 ms/99.999%
Traffic jam	Density/throughput/availability	480 Gbps/km2/100Mbps (DL) 20Mbps (UL)/95%
AR/VR	Latency/throughput	<7 ms/4-8 Gbps
Broadband to the home	Density	4000 devices/km2 or 80Gbps km2

Table 0-1: Detailed Description of 5G Requirements per Use Case, Source: Ericsson

However, 6G networks are set to extend eve more the aforementioned 5G requirements due to the even more enhanced capabilities that they will bring to support the even extended user requirements. It is significant to point out that 6G standardization is in its early phases currently and the expected IMT-2030 regulation is to set all the 6G-relevant requirements and use cases. However, the need for new service types beyond the 5G ones (eMBB, uRLLC, mMTC) has been identified. As described in [3] and [4] these are:

- **Computation Oriented Communications (COC)**, where distributed and in-network computation enabled by federated learning and edge intelligence, will provide the relevant service provisioning, and define the quality of service (QoS) flows to maximize also computational accuracy.
- **Contextually Agile eMBB Communications (CAeC)**, which extends 5G eMBB to be more agile and adaptive to the network environment, the physical environment, and the social environment.
- **Event Defined uRLLC (EDuRLLC)**, where 5G uRLLC is extended to support uRLLC in extreme or emergency scenarios where user density, traffic patterns, mobility models and spectrum availability is dynamically changing (opposite to 5G, where uRLLC is performed in static environment conditions).

1.3 Enabling Physical Layer Technologies for 5G/B5G Networks

In this paragraph the key enabling PHY technologies that are of significant interest concerning 5G/B5G networks are briefly introduced. In this framework sub-paragraph 1.3.1 focuses on m-MIMO orientations, sub-paragraph 1.3.2 introduced NOMA, sup-paragraph

1.3.3 presents Relay Nodes and 5G sidelink communications, while sub-paragraph 1.3.4 introduces Reconfigurable Intelligent Surfaces (RIS).

1.3.1 Millimeter Wave transmission

As we have mentioned before, the 5G/B5G ecosystems are based on the latency, capacity and throughput requirements that IMT-2020 has established. In order to meet these increased demands in terms of the above metrics, 5G/B5G systems make extensive use of more frequency bands than the previous generation systems (e.g., 4G).

Until now, modern era communication systems are operating in the UHF (Ultra Hugh Frequency Band) band. This spectrum zone is called centimeter Waves (cmWaves) and contain frequencies from 300 to 3,000 MHz (1–0.1 m). The mmWaves concern the EHF (Extremely Hugh Frequency Band) that lies between 30 and 300 GHz (1-10 nm). Although research interest in that areas, are expressed in lower bands (above 6 GHz) [5]. In Figure 3, the operation bands of 5G are displayed.

Band	Frequencies
L	1 – 2 GHz
S	2 – 3 GHz
S	3 – 4 GHz
C	4 – 6 GHz
C	6 – 8 GHz
X	8 – 10 GHz
X	10 – 12,4 GHz
Ku	12,4 – 18 GHz
K	18 – 20 GHz
K	20 – 26,5 GHz
Ka	26,5 – 40 GHz

Table 0-2: The mmWave spectrum

The high demand and scientific interest in that field comes from the criteria of low latency, huge capacity and extremely throughput that the 5G (and Beyond) require.

One major issue for these bands is the existence of many physical (PHY) layer challenges. These challenges concern about high propagation loss, directivity, sensitivity to blockage and dynamics due to mobility of UE's given the enhanced coverage area [6].

These challenges are not so visible in the satellite and P2P (point-to-point) backhaul communications that have not such requirements of a lot of user coexistence in an area. In these areas these frequency band have been used from years before. Although, these challenges -during the past- made impractical the use mmWaves in cellural telecommunication networks. Nowadays, the overcoming of these limitations came from the antenna theory and RF design. High-gain, directional and spread spectrum antennas have been developed. In that way, high level of throughput can be established, despite the simultaneous presence of a variety of users in the coverage area's macro or nano-cells [7], [8].

1.3.2 Massive Multiple-Input-Multiple Output Antenna Orientations

MIMO antenna orientations consist of antenna arrays with multiple elements both at the transmitter and receiver ends. These systems belong to the broader category of smart or adaptive antennas, where multiple antennas are combined with advanced signal processing and analysis techniques to increase the capacity of the wireless channels by exploiting the phenomenon of multipath propagation that characterizes wireless communication links. It is crucial to note that the term "input" refers to the transmitting antennas, i.e., the input to the system via the transmitter, while the term "output" refers to the receiving antennas - the terminal equipment of the receiver. The significance and wide acceptance of MIMO systems lie in the fact that they greatly increase the system's capacity by offering significant diversity gains and/or multiplexing gains without increasing the utilized bandwidth or the transmission power.

LTE technologies (especially the mmWaves) have established the need of using antenna systems that allow to a large number of users to be served at the same time. The 4G-LTE systems use MIMO antennas (with 2 or 4 elements) in order to achieve peak data rates of the order of 1000 Mbps for the downlink and 500 Mbps for the uplink.

The need of combination between mmWaves and MIMO systems can be shown by the application of Friis' equation for free space losses, in GHz frequencies. By doing this we observe that given an average steady distance between transmitter and receiver, the signal power is 1000 times reduced compared with the current 4G-LTE signals [9]. The solution is to use ultra-directional antennas with dimensions relevant τo millimeters. In other words the coexistence of beamforming techniques and MIMO antennas, which pack a huge number of elements onto a small cell, compensate the high levels of attenuation give the above approach [10].

According that framework, 5G New Radio, introduced the concept of massive MIMO (m-MIMO), which - as the name implies - includes the application of MIMO technology on a much larger scale for greater coverage and network capacity. m-MIMO uses many more transmitting and receiving antennas to increase transmission gain and spectral capacity. In 5G cellular networks, multi-user (MU) MIMO systems are used. There are also SU-MIMO systems and baseband MIMO systems, which are used commonly in the backhaul of the telecommunication networks. In Fig. 1-4 a typical multi-user (MU-MIMO) system can be shown.

Although no specific minimum number of antennas is required to implement m-MIMO, the generally accepted limit for a system is eight (or more) transmitting and eight (or more) receiving antennas. The latest research attempts in the R&D field extended the antenna elements to dozens or even hundreds of them.

We should also highlight some key characteristics of the (Massive) MIMO Systems:

- As we highlighted this technologies uses many more antennas than the number of UEs in the cell. In that case the beam is much narrower, allowing the base station to deliver RF power to the UE with greater accuracy and efficiency. The phase and gain of the antenna are controlled separately, with the channel information remaining at the base station, simplifying the UE without adding multiple receiver antennas. Installing a large number of base station antennas will increase the signal-to-noise ratio in the cell, leading to higher capacitance and cell position efficiency. Since the huge MIMO 5G application is in mmWave frequencies, the required antennas are small and easy to install and maintain [11].
- However, for RF engineers, MIMO and beamforming at mmWave spectrum insert many new challenges. The 5G NR standards provide to the physical framework framework structure, a new benchmark and new transmission modes to support 5G enhanced (Embb) mobile data rates. Designers need to understand 3D beam patterns and ensure that the beams can be connected to the base station and offer the desired performance, reliability and user experience.
- To implement MIMO and configure the structure on 5G base stations, designers must carefully select hardware and software tools to simulate, design, and

test highly sophisticated systems containing dozens or even hundreds of antenna components. Engineers will use active phase array antennas to implement MIMO and beam configuration on base stations and devices. Not only are active antennas necessary to overcome signal propagation issues, such as higher path loss at mmWave, but they also provide dynamic configuration and beam guidance to specific users. Active antennas offer more flexibility and improve the performance of 5G communications.

- On the other hand, the development of active phase antennas in commercial wireless communications represents a significant change from the passive antennas used in previous generations. MIMO and beamforming technologies increase capacity and coverage in a cell. For 5G devices and base stations, multi-antenna techniques require support in many frequency bands - from sub-6 GHz to mmWave - and in many scenarios, including huge IoT connections and extreme data performance.
- Radar and satellite communications for aerospace and defense have long used active phase antennas, but these antenna arrays tend to be large and very expensive. Applying this technology to commercial wireless - where antenna arrays should be much smaller and less expensive - introduces many new challenges. There is a long list of required 3GPP tests for base stations, including transmitter tests and radiation receiver tests. Depending on the configuration of the base station, some FR1 tests require radiation tests and all FR2 tests require radiation tests.
- Almost all 5G MIMO tests require over-the-air (OTA) testing. Early in development, OTA test solutions should characterize 3D beam performance across antenna bandwidth, including aspects such as antenna gain, sidelobe, and zero depth for full bandwidth and 5G bandwidth.

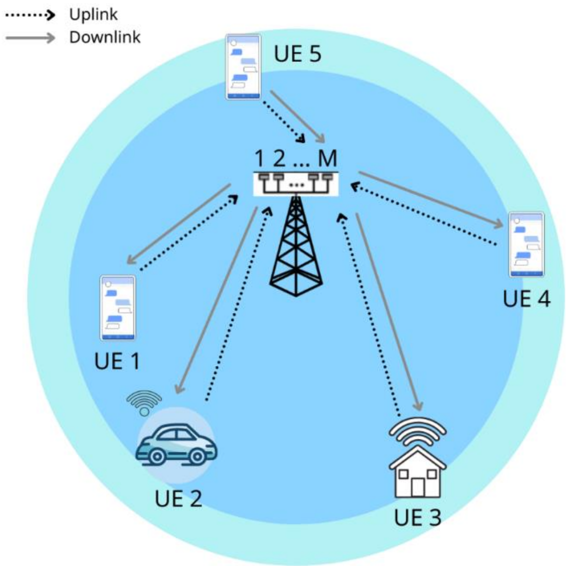


Figure 0-4: MU-MIMO system

To conclude this section it is crucial τo dive into the basic theory of MIMO systems. If we assume a static channel in an $N_t \times N_r$ MIMO system as depicted in Fig. 1-5, where N_t is the number of transmitting antennas and N_r is the number or receiving ones, with ideal channel conditions and constant response or flat-fading channel, the output can be described by the equation:

$$y = H \times s + n \; (1)$$

where $s = [s_1 \ldots s_{N_t}]^{\mathrm{T}}$ is the vector of N_t transmit signals, $y = [y_1 \ldots y_{N_r}]^{\mathrm{T}}$ is the vector of N_r receiving signals, and $n = [n_1 \ldots n_{N_r}]^{\mathrm{T}}$ is the noise vector consisting of N_r independent elements (corresponding to the receive antennas), which can be modeled as samples from a Gaussian distribution. The matrix $H = [h_{\mathrm{ij}}]$ is an $N_t \times N_r$ matrix that contains the complex channel coefficients for each possible combination of channel between the i-th transmitting antenna and the j-th receiving one. In the case of a static channel, this matrix is given by:

$$H = \begin{bmatrix} h_{11} & \cdots & h_{1N_r} \\ \vdots & \ddots & \vdots \\ h_{N_{t_1}} & \cdots & h_{N_t N_r} \end{bmatrix} (2)$$

MIMO systems are divided into three main categories based on their primary functions: Precoding and Beamforming systems, Spatial Diversity systems, and Spatial Multiplexing systems. The latter two are widely used in current technology due to the multiple gains they provide.

Based on the standards set by ITU, ETSI, and 5GPP (5G New Radio), the concept of m-MIMO is introduced, which applies MIMO technology on a much larger scale to achieve greater network coverage and capacity. m-MIMO utilizes a significantly larger number of transmit and receive antennas to increase transmission gain and spectral efficiency. To achieve substantial capacity gains in MIMO, multiple mobile terminals need to generate simultaneous uplink traffic.

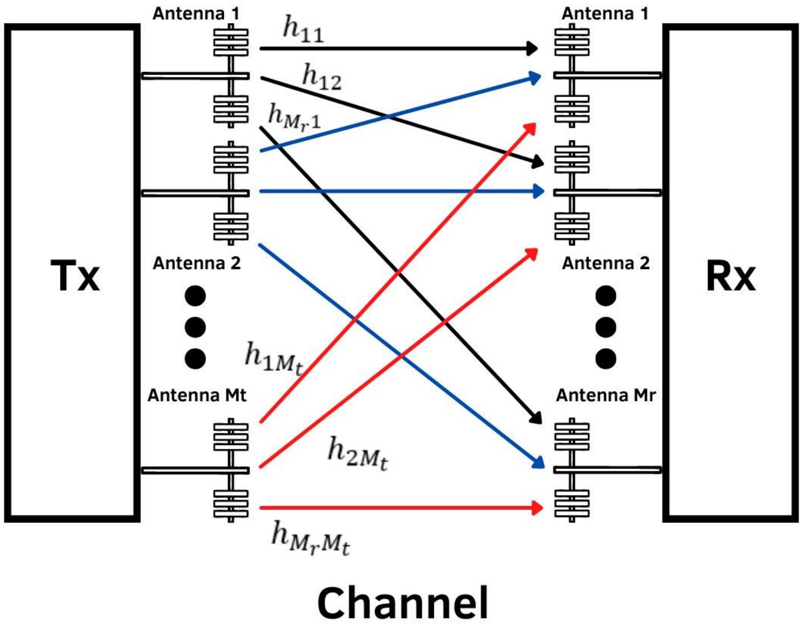


Figure 0-5: Block diagram of a $N_t \times N_r$ m-MIMO system

In 6G systems, where killer applications will be AR/VR and holographic communications, the need for large data transmission, results in a need for a very high-frequency band to support the increasing service scenarios demands [12]. THz and sub-THz bands have been proposed as a potential solution towards this direction. These bands are spread from 0.1 to 10 THz [13]. However, several challenges have been witnessed in these scenarios. First of all, such a high-band transmission can serve really short-range coverage. Thus, ultra-massive MIMO antenna systems in BSs should be used and BSs should be located near to each other. Limitations can, also, be witnessed concerning hardware availability, transmission power, and increased pathloss [12]. The following enabling MIMO technologies are of interest in 6G networks:

- Ultra-massive MIMO: Antenna arrays can contain over 10,000 very small antenna elements, forming ultra-narrow band beams. In this way, pathloss considerations can be mitigated. Moreover, by the formulation of hundreds of beams the system capacity can be increased and a large number of users can be supported. Furthermore, co-channel interference is also mitigated due to the narrow-band nature of the links [5]. However, the necessity of deploying a lot of antennas over short distances may lead to mutual correlations between each other.
- Cell-free (CF) mMIMO: A promising technique to mitigate interference between neighboring cells, which are deployed close to each other in 6G orientations, is CF mMIMO. In such case, Access Points (APs) are spread in the coverage area to support UEs that demand service. A central processing unit (CPU) maps UEs to APs. This technique has great influence when CSI changes, even in the order of milliseconds in 6G, which means that certain system parameters become quickly obsolete. In particular, CF mMIMO systems result in negligible effects of small-scale fading by exploiting channel hardening [7]. Also, in the case of CF mMIMO, the probability of coverage is higher. In this direction, given that as the number of users increases, the total training time is significantly prolonged. Moreover, APs are equipped with a smaller number of antennas resulting in less demanding power requirements. However, a drawback that has been identified in some research efforts [7] is that as network size increases, limitations can exist in the scalability of this approach.

1.3.3 Non-Orthogonal Multiple Access (NOMA)

The objective and purpose of wireless communications networks (especially in 5G/B5G) is to serve multiple users in a geographic area, according to their requirements for QoS and QoE. Multiple access refers to the simultaneous access of multiple users to the same radio resources. It is understood, therefore, that the term pertains to systems and users that have both geographical relevance (i.e., they are located in the same geographic area) and frequency relevance. Additionally, a fundamental goal of the multiple access process is for the user to perceive the service at a continuous rate and with the required QoS and QoE. The system's capacity essentially reflects the number of users that can be served by the respective system with the required QoS threshold. The main types of multiple access are the following:

1. Frequency Division Multiple Access (FDMA): In FDMA, the available frequency spectrum is divided into multiple non-overlapping frequency bands, and each user is allocated a specific frequency band for communication.
2. Time Division Multiple Access (TDMA): In TDMA, users share the same frequency band, but they are allocated different time slots. Each user occupies a specific time slot to transmit their data.
3. Code Division Multiple Access (CDMA): In CDMA, users share the same frequency band and the same time slots. However, each user is assigned a unique spreading code that allows their signals to be separated and distinguished at the receiver.
4. Orthogonal Frequency Division Multiple Access (OFDMA): OFDMA is an extension of FDMA where the frequency band is further divided into multiple

orthogonal subcarriers. Users can be allocated subsets of subcarriers to transmit their data simultaneously.

These multiple access techniques enable efficient utilization of the available resources and allow multiple users to share the network effectively while maintaining the required QoS levels.

However, Orthogonal techniques (OFDMA) present relatively good results, but at the expense of the SE levels, which contradicts the fundamental requirements of the new generation of wireless networks (5G). For this reason, new enhanced technologies have been developed in this direction, such as NOMA, which, unlike conventional OFDMA technologies, is based on non-orthogonal resource allocation. This technique allows multiple users to share the same time and frequency resources (see also Fig. 1-5) through power domain multiplexing (Power Domain NOMA) or code domain multiplexing (Code Domain NOMA). In the first case (PD-NOMA), different power levels are assigned to different users based on their channel conditions to achieve high system capacity. In the second case (CD-NOMA), multiplexing is achieved using sparse (or low correlation) spreading sequences for the transmission of each user's data streams. Although CD-NOMA provides the potential for significant SE improvement, it requires a wide transmission bandwidth and is not easily applicable to current systems. On the other hand, the implementation of PD-NOMA is relatively straightforward, as it does not require significant changes to existing networks and infrastructures.

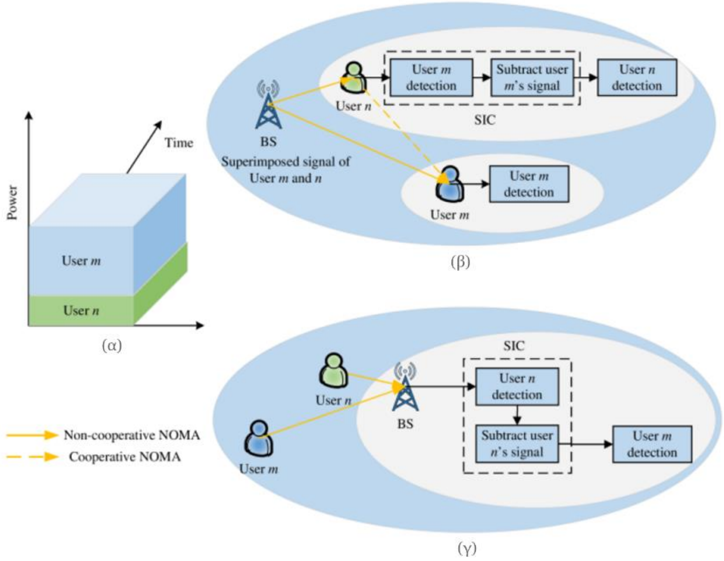


Figure 0-6: Spatial Multiplexing, NOMA techniques (a) PD-NOMA, (b) CD-NOMA

1.3.4 Relay Nodes and 5G Sidelink

RNs are elements of the cellular network that can extend the radio coverage (cell range extension) and belong to the broader category of heterogeneous networks (HetNets). Their use in next-generation networks (5G/B5G) is crucial due to the simultaneous existence of multiple users and their distribution even in areas without network coverage. RNs are not simple repeaters, in which the signal is received and retransmitted along with the accompanying noise, but rather a Layer 3 (L3) structure where the initial stages of decoding/demodulation and re-encoding/remodulation take place, resulting in an improvement of the received Signal-to-Noise Ratio (SNR). The communication between the BS and the user equipment (UE) is achieved through at least one relay (at least 2-hop communication), transparently to the user (without their awareness), using the RN's own cell-ID and synchronization signals, both in the uplink (UL) and downlink (DL). The UE's service is provided using system resources, which are managed by the BS. A BS that is connected to a UE through an RN is called a Donor BS. The architecture of a 5G/B5G system where RNs are utilizes is depicted in Figure 1-7.

The three main advantages of RN-enabled wireless communication's systems are the following:

1. It is a cost-effective way to extend the network's radio coverage (cell edge or dead zones) and support locally increasing capacity demands (hot zones) without the need for wired backhaul connection to BS, avoiding additional installation costs and high energy consumption. Due to their small size, RNs can be installed on streetlight poles or tall buildings to ensure Line of Sight (LOS) with the BS.
2. RNs can be mobile, adding flexibility to the cellular network. They can be used to cover emergency needs and increased capacity requirements, as well as to provide high-speed services. RNs perform the necessary relays between BSs, while UEs maintain the connection with the RN, allowing reduced control overhead in the network and extended battery life for users.
3. RNs can be used in a multi-hop network configuration to support remote users, not only through a single hop (2-hop) but also through multiple RNs.

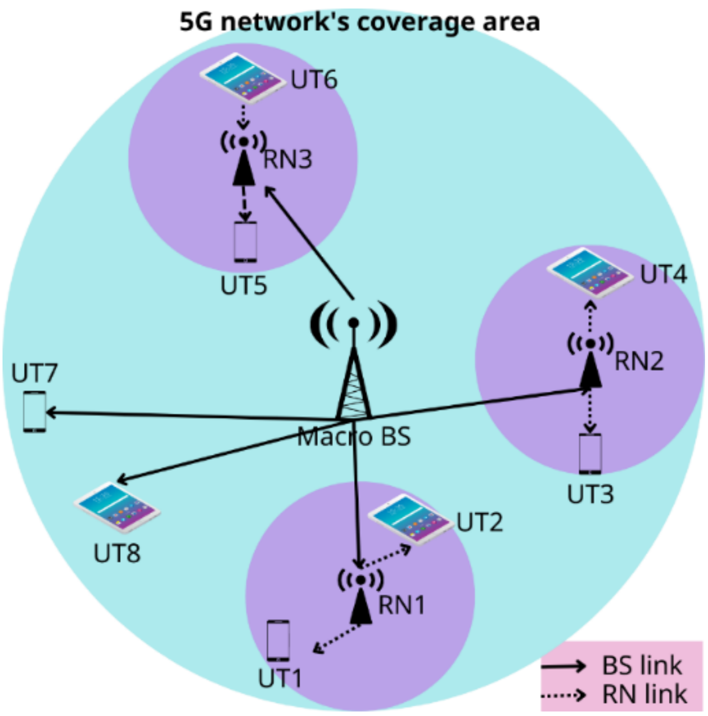


Figure 0-7: RN-enabled 5G/B5G topology

There are different types of relay nodes categorized based on the spectrum or protocols used:

1. Spectrum-based categorization:
   a) ***Inband RNs***: They utilize the available radio frequency spectrum used by the BSs in the cellular network, simply relaying the signals to the intended users.
   b) ***Outband RNs***: They are assigned additional spectrum to serve users not covered by existing BSs.
2. Protocol-based categorization:

a) ***Amplify & Forward (A&F) RNs***: RNs in this category amplify the received signal and forward it to UTs without additional processing. Amplification is a straightforward solution with the main advantage of introducing minimal delay. However, there is no improvement in the signal-to-interference-plus-noise ratio (SINR) as both noise and interference are also amplified.

b) ***Decode & Forward (D&F) RNs***: In this case, the signal from the base zone originating from the BS is initially decoded, then encoded again before being forwarded to UTs. The main drawback of the D&F protocol is the delay in retransmitting the received signal, which is due to the demodulation/modulation and signal processing operations. However, the D&F strategy exhibits high performance compared to the A&F scheme.

Except RNs, another enabling technology in 5G that can ensure high reliability and network KPIs improvements, is the direct D2D communication between devices, also referred as 5G sidelink. D2D communications can act separately or in cooperation with RNs in order to improving reliability, and enhancing capacity of 5G orientations. Moreover, in this way metrics such as energy efficiency (EE) and spectral efficiency (SE) can be also improved by the reduction of the overall systems' transmit power and the efficient resource sharing. Moreover, the number of connected mobile and/or IoT devices can be maximized. It is, also, significant that the joint utilization of direct D2D communications and advance PHY layer techniques such as mmWave transmission, mMIMO, advanced precoding and beamforming and OFDMA, NOMA, can further improve the aforementioned metrics.

3GPP has been developing standards for sidelink as a tool for UE to UE direct communication required in various use cases since LTE. The following significant interest has been observed based on the several motivations for sidelink enhancements [13]:

1. **Power saving** enables UEs with battery constraint to perform sidelink operations in a power efficient manner. This is in line with enhanced radio resource allocation. Rel-16 NR sidelink is designed based on the assumption of "always-on" when UE operates sidelink, e.g., only focusing on UEs installed in vehicles with sufficient battery capacity. Solutions for power saving in Rel-17 are required for vulnerable road users (VRUs) in V2X use cases and for UEs in public safety and commercial use cases where power consumption in the UEs needs to be minimized.
2. **Enhanced reliability and reduced latency** allow the support of URLLC-type sidelink use cases in wider operation scenarios. The solution should be able to operate in-coverage, partial coverage, and out-of-coverage and to address consecutive packet loss in all coverage scenarios. The system level reliability and latency performance of sidelink is affected by the communication conditions such as the wireless channel status and the offered load, and Rel-16 NR sidelink is expected to have limitation in achieving high reliability and low latency in some conditions, e.g., when the channel is relatively busy.

The objective of developing radio solutions necessary for NR sidelink enhancement is primarily to support advanced V2X services, public safety services and other commercial use cases related to NR sidelink.

1.3.5 Reconfigurable Intelligent Surfaces

RIS is proposed as an efficient solution to enhance connectivity in 6G networks, taking into account the hardware and deployment costs. As depicted in Fig. 1-7, a RIS-assisted wireless link, utilizes an intelligent surface, which is composed of several three-dimensional

(3D) reflection units, between the BS and the UE. Thus, intelligent beamforming is achieved by the relevant dynamic adjustment either in the amplitude or the phase of the incoming signal. RISs have a relay role in end-to-end communication, and, as a sequence, they can efficiently be used in blind network spots or to extend the coverage area of the network [14], [15].

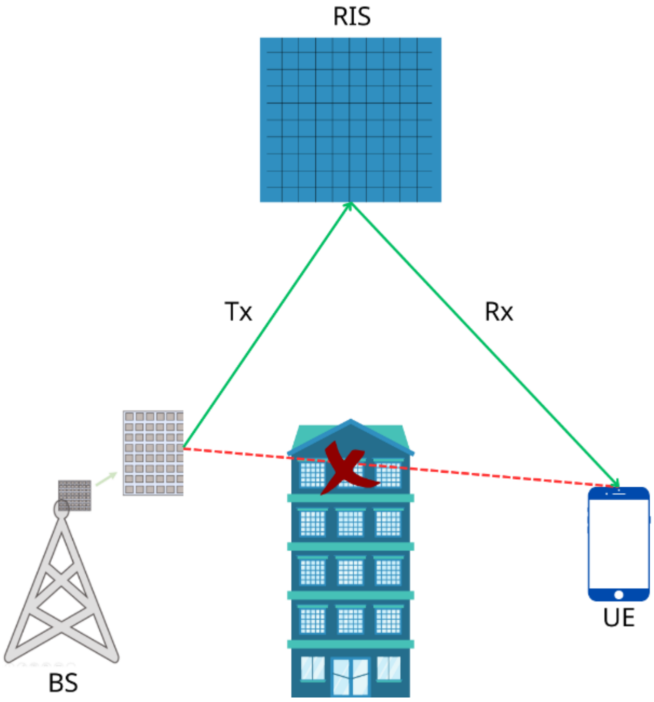


Figure 0-8: RIS-aided 5G/B5G communications

Chapter 2: Machine Learning and Deep Learning Principles for 5G/B5G Networks

In this chapter the principles of ML are exposed. In this framework, a classification of ML techniques is presented. Moreover, due to the data overload in today's 5G networks, the significance of DL techniques, which are based on large datasets containing big amount of data is, also, highlighted. Finally, MEC and distributed ML techniques are, also, discussed due to the arising need for distributed computation using different 5G/B5G networks' entities (BSs, UEs, servers, CN, etc.) with different computation characteristics. The goal of these techniques is to reduce data traffic from the CN and share the computation task among networks' entities. In paragraph 2.1 an introduction to ML techniques is presented. Paragraph 2.2 discusses the classification of ML techniques, where supervised, Unsupervised and RL principles are presented. Paragraph 2.3 focuses on DL and DRL techniques, while paragraph 2.4 describes how MEC and distributes ML techniques are utilized in 5G/B5G networks using, also, the techniques that are presented in the previous paragraphs.

2.1 Introduction to ML and basic principles

ML is a branch of artificial intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn and make predictions or take decisions without being explicitly programmed. It involves the construction and study of models that can automatically learn from the given datasets or even the training environment itself, and thus, improve with experience. At its core, machine learning relies on statistical techniques and mathematical models to analyze and interpret complex patterns and relationships in data. By training on labeled or unlabeled data, machine learning algorithms can identify and generalize patterns, enabling them to make predictions or take actions based on new, unseen data.

One of the first researchers that defined the term Machine Learning was Tom M. Mitchell, who has been described as one of the major machine learning pioneers, in [16], [17]. According to that definition *"Machine learning is the study of computer algorithms that allow computer programs to automatically improve through experience"*.

A basic characteristic of ML algorithms is that they learn by experience, similar to how humans do. For example, after having seen multiple examples of an object, a compute-employing machine learning algorithm can become able to recognize that object in new, previously unseen scenarios.

However, nowadays ML has been extremely popular in every aspect of research and enterprise activity. This happens because it constitutes a scalable way to solve complicated real-world. The event that sparked the growth of ML has been the dramatic change in data storage and computing processing power of the computer systems. We can assume that as more people are increasingly becoming involved to ML activities, the expectations for ML-based algorithms are to continue with this route and cause amazing progress in different fields.

A more systematic definition for ML, which will help us out to the classification or the used ML algorithms is the following according to [18]:

"A machine learns the execution of a particular task T, with the goal of maintaining a specific performance metric P, based on a particular experience E, where the system aims to reliably improve its performance P while executing task T, again by exploiting its experience E".

According to their purpose and the policy that they adopt in term of the way to achieve the above, the basic categories of ML algorithms are shown in Figure 2-1 and further analyzed in the next paragraph.

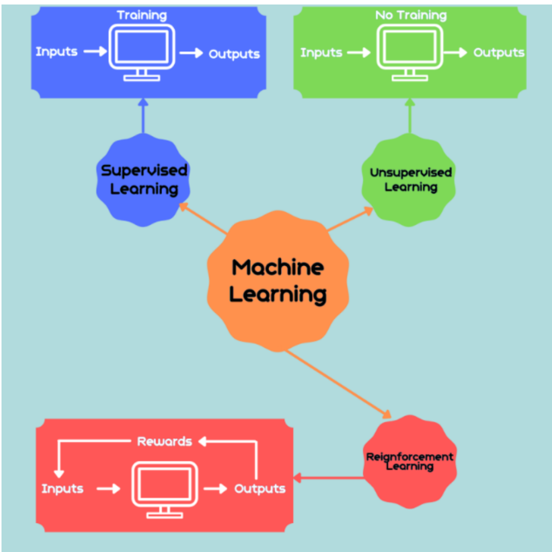


Figure 0-1: Different Types of Learning

2.2 Types of Learning

The purpose of the present thesis is to analyze the need for ML-based schemes for RRM in 5G/B5G networks. Thus, in order to present, in the following chapters, that need and discuss the existing literature concerning the use of ML in resource allocation in 5G/B5G networks, this sub-paragraph first introduces the classification of ML algorithms, in terms of the type of data they process (labeled or unlabeled), as well as in terms of the corresponding mechanisms. Sub-pagraph 2.1.1 refers to Supervised Learning, sub-paragraph 2.1.1 to Unsupervised Learning, while sub-paragraph 2.1.3 discusses RL.

2.2.1 Supervised Learning

Supervised learning is based on a dataset with values accompanied by their respective labels. These labels can be produced either by humans or automatically by computation [19] (see also Fig. 2-2). A common practice to deal with the dataset is to split it in a training and a test set, where the first one is used for model training. In other words, a mapping between the inputs and the labels is being produced. The most indicative use cases of supervised learning are classification or regression problems. The latter term refers to the prediction of a target numerical value, given a set of features/attributes, also called predictors, through an estimation function. In linear regression the estimation function is linear, while in logistic regression it is a common sigmoid. Classification refers to the prediction of a class label, by using classified example data as input. The basic difference, compared to regression techniques, is that the model displays the probability that a certain value belongs to a given class [18]. The system is trained by multiple examples of a class, along with their labels, in order to learn how to classify new instances. The ML techniques/algorithms, that are mostly used in RRM-related problems, are briefly presented below and will be reported again in section IV, where the corresponding literature is analyzed in detail.

A *k-NN* algorithm classifies instances by comparing its *k* nearest neighbor's labels. Then, the item is classified to the most common of them [20], [21]. On the other hand, Support Vector Machines (SVMs) are used for both classification and regression. Data are plotted as a point in an n-dimensional space, where n is the number of features of the dataset, and classified by finding the hyper-plan, which differentiates the problem's classes in an optimal way [22]. Decision trees can be used, either for regression or classification purposes. However, traditional decision trees approaches record high variance levels, due to their sensitivity to training data. Aiming to prevent this problem, alternative approaches are implemented. For instance, bagging trees classifiers use bootstrap simulations to generate reliable results [23]. A major category of supervised learning techniques is the artificial neural networks (ANNs). These learning algorithms are inspired by brain, in order to simulate, predict or store information. Their basic building units are neurons and the connections between them, which formulate the model. ANNs are used both in regression and classification problems.

Furthermore, overfitting/underfitting should be checked at each time a model is formed, in order to prevent inserting errors, making it unable to depict properly all the attributes of the tested dataset. Underfitting occurs when the model is not able to obtain a low error on the training set [24]. This means that the model cannot describe all the characteristics in the dataset. On the other hand, overfitting takes place, when a significant difference between the errors in training and implementation (training set vis a vis test set) is detected [25]. This means that the model describes more characteristics, than the actual ones.

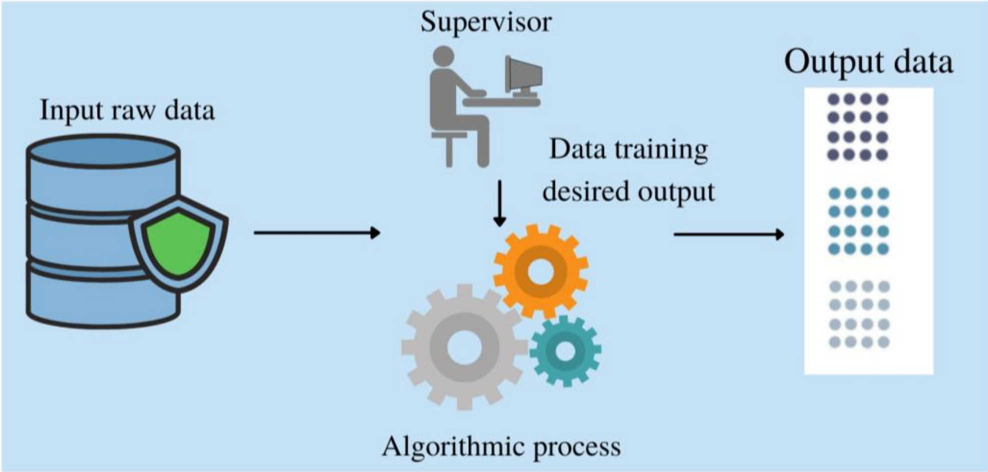


Figure 0-2:Supervised Learning

2.2.2 Unsupervised Learning

Unsupervised Learning differs from supervised learning (see Fig. 2-3), as the model itself tries to identify the common characteristics of the dataset [18], [25]. Moreover, labels are not included in the dataset, as the system tries to find them without external help. However, the concept of training and test data remains the same. The key aspects of unsupervised learning are summarized as follows [26], [27], [28]:

1. Clustering: Clustering is a common task in unsupervised learning, where the goal is to group similar data points together based on their inherent similarities or patterns. Algorithms such as *k-Means* clustering, hierarchical clustering, and Gaussian mixture models are used to identify clusters within the data.
2. Dimensionality Reduction: Dimensionality reduction techniques aim to reduce the number of features or variables in a dataset while preserving its essential information. This helps in visualizing and analyzing high-dimensional data and can also improve the performance of machine learning algorithms. Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding are popular dimensionality reduction techniques.
3. Anomaly Detection: Anomaly detection involves identifying rare or unusual instances in a dataset that differ significantly from the majority of the data. Unsupervised learning algorithms can learn the normal patterns from unlabeled data and flag any observations that deviate from the learned patterns as anomalies. This is useful in various applications such as fraud detection, network intrusion detection, and equipment failure prediction.
4. Association Rule Learning: Association rule learning aims to discover interesting relationships or associations between different items in a dataset. It is commonly used in market basket analysis to identify frequently occurring item combinations, such as "people who buy diapers are likely to buy baby wipes." Apriori algorithm and FP-growth algorithm are commonly used for association rule mining.
5. Generative Models: Unsupervised learning includes generative models that learn the underlying probability distribution of the data. These models can then generate new samples that resemble the original data distribution. Examples of generative models include autoencoders, generative adversarial networks and autoencoders.

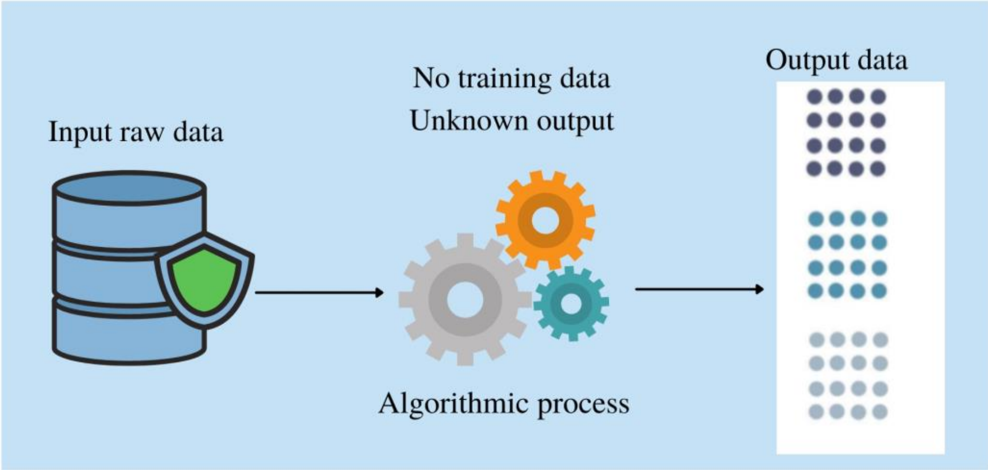


Figure 0-3: Unsupervised Learning

2.2.3 Reinforcement Learning

RL is an ML category which is based on the interaction and communication with the learning environment to train and validate effective models (see also Fig. 2-4). This is achieved by the utilization of a learning entity called software agent. The information feedback that the agent returns to the model is called rewards (positive case) or penalty (negative case). In that way, the agent creates a policy to set up its own learning scheme and decide which actions to choose in a certain situation. The scope of an effective RL model is to maximize the cumulative rewards over time [29]. There are several known RL schemes such as state-action-reward-state-action [30], Q-learning [31], Deep Q-learning (DQL) [32], deep deterministic policy gradient [33] and asynchronous advantage actor-critic algorithm [34]. However, the most widely used RL algorithms are Q-Learning and deep Q-Learning, which combines Q-learning and neural networks.

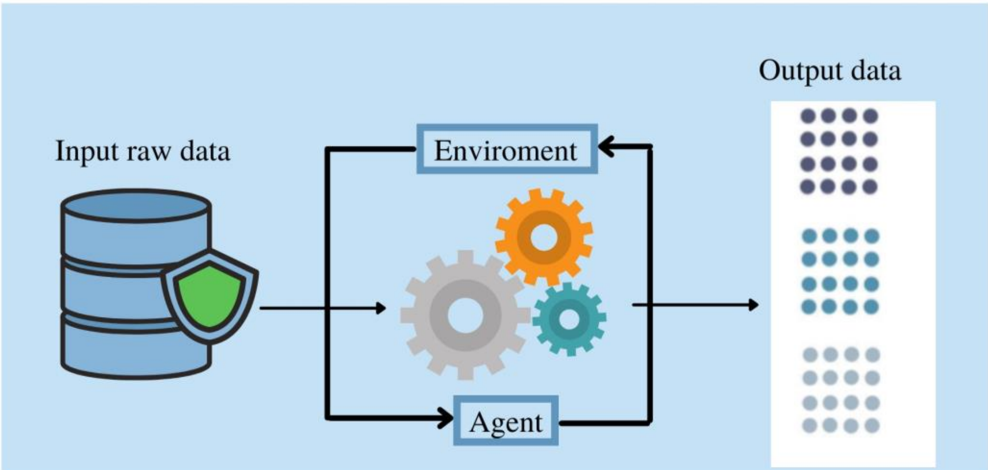


Figure 0-4: Reinforcement Learning

The Q-Learning algorithm has been proposed as an efficient way to deal with rapidly changing and non-linear environments. For this purpose, Q-Learning fits perfectly in the 5G/B5G wireless network domain. The cellular environment is characterized by complex propagation models, increased interference levels, dense connections and high user mobility, making Q-Learning a promising approach to solve complex optimization problems which have to do among others with resource allocation, power management and RN or BS selection.

A typical Q-Learning environment is depicted in Fig. 2-5. The agent (Q-function) collects feedback from the environment and takes some action that will later affect the environment. In other words, there is a set of potential states and a set of potential actions that can be performed. The agent specifies the transitions between states, based on the actions, aiming to maximize reward. Q-function is mathematically formulated as follows [33], [34]:

$$Q'(s_t, a_t) \leftarrow Q(s_t, at) + a \times (r_t + \gamma \times maxb(Q(s_{t+1}, b) - Q(s_t, a_t)), b \in A \quad (3)$$

where Q' is the updated Q value, s_t is the state at the current time interval and s_{t+1} is the state at the next time interval. Moreover, α is the learning rate and rt is the reward received from the network when moving from the state s_t to state s_{t+1} and A is the Q-table that stores all the actions. Moreover, γ is the discount factor which determines the importance of future rewards. In fact, $0 \leq \gamma \leq 1$, where a zero value means that only current rewards are considered, while a discount factor close to one means that long-term high rewards are of interest.

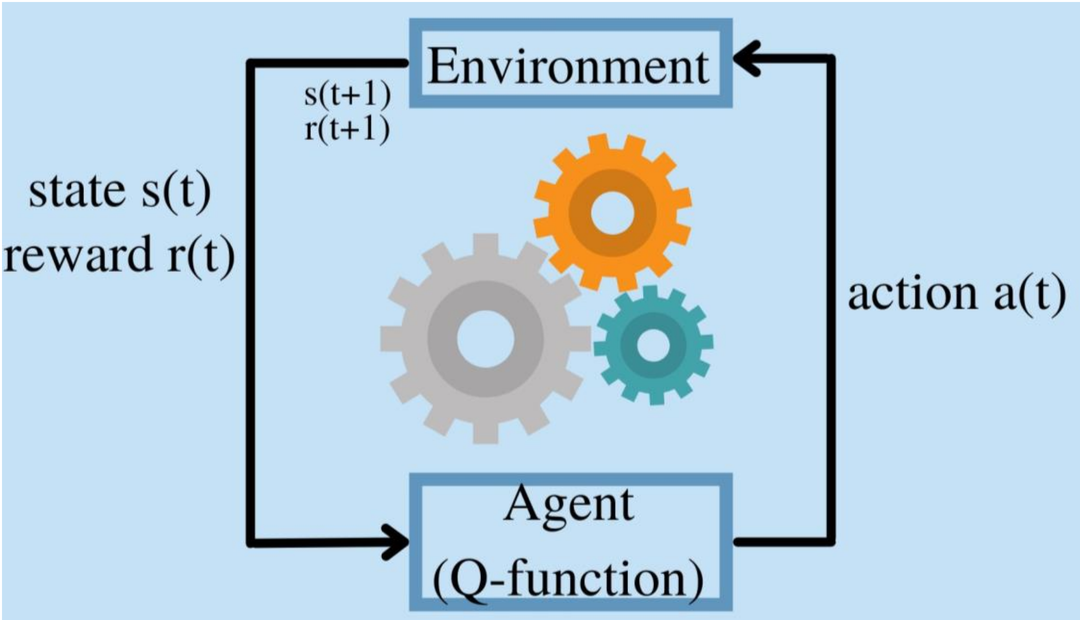


Figure 0-5:Q-Learning

2.3 Deep Learning

Deep Learning (DL) is a subset of ML that focuses on training ANNs with multiple layers, also known as deep neural networks (DNNs), to learn and represent complex patterns and relationships in data. It is inspired by the structure and function of the human brain, specifically the interconnected network of neurons.

One of the key advantages of deep learning is its ability to automatically learn hierarchical representations of data. Each layer of a DNN learns progressively more abstract features, allowing the network to capture intricate patterns and dependencies in the input data. This hierarchical feature learning enables DL models to excel in tasks such as image and speech recognition, natural language processing, and generative modeling [35].

Recent advancements in deep learning have been driven by the availability of large-scale labeled datasets, significant improvements in computational power, and breakthroughs in NN architectures and training algorithms. Some key categories of DNNs include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks [36].

Moreover, DL has benefited from innovations in regularization techniques, optimization algorithms, and the integration of domain knowledge into neural network architectures. Transfer Learning (TL) and pretraining strategies, such as using pretrained models or leveraging self-supervised learning, have also played a crucial role in improving the performance of deep learning models, especially in scenarios with limited labeled data.

2.3.1 Deep Reinforcement Learning

Deep reinforcement learning (DRL) is a subfield of AI/ML that combines DL techniques with RL ones. It involves training artificial agents to learn optimal decision-making policies through interaction with an environment. DRL leverages DNNs to approximate complex value functions or policies that map observed states to actions.

As presented in paragraph 2.1.4 in traditional RL schemes, agents learn from scalar rewards provided by the environment. However, in DRL, DNNs are used to process high-dimensional input, such as raw sensor data or images, enabling the agent to learn directly from raw sensory inputs without handcrafted feature engineering.

Thus, in NP-Hard problems in 5G/B5G RRM domain (such as RN placement and selection), when utilizing m-MIMO antenna configurations and advanced physical layer techniques such as OFDMA or NOMA, advance precoding and beamforming, the Q-table with the full set of potential actions, states and rewards can be large enough. This can exponentially increase the optimization problem's complexity, which comes against the major 5G/B5G requirement for low latency responses. In such cases, a NN can be trained to map the set of states with the best-performing action or in other words to perform the Q-function approximation. This RL technique is called DQL and is widely proposed due to its' ability to decrease the amount of the state-action duplets of the tabular-based Q-Learning algorithm, and, thus, produce more generalized models in optimization tasks [37], [38].

Based on Equation (3), a DQL agent aims to gather all the related information from the environment by minimizing the so-called temporal difference (TD) function [39], between the next Q-value $rt + \gamma \times maxb(Q(st+1, b)), b \in A$ and the current Q-value $Q(st, at)$. For this purpose, the DQL's basic characteristic is to utilize two approximators (NNs). The first one is used to estimate the current best action, while the latter is used to predict the next action. A typical DQN structure is depicted in Fig. 2-6.

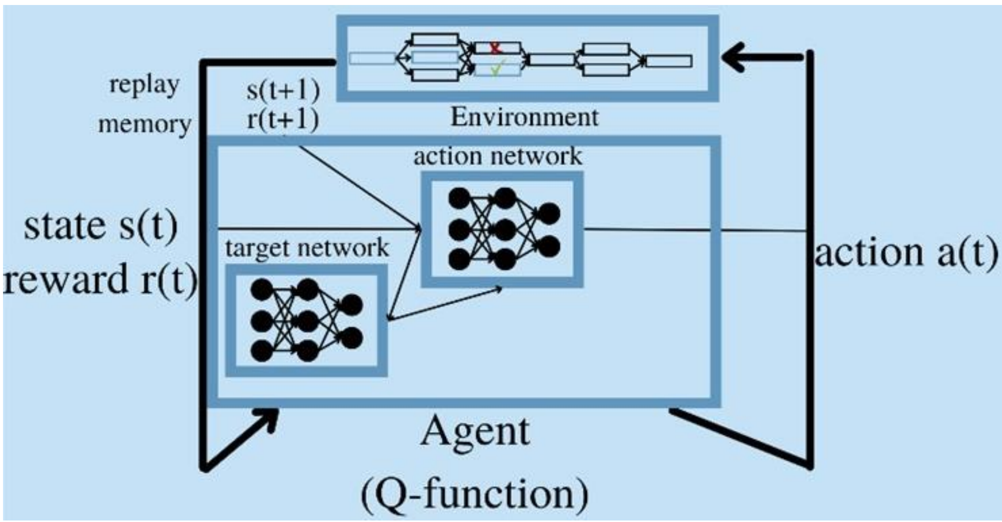


Figure 0-6: DQL methodology

2.4 Distributed Learning and Mobile Edge Computing

An important bottleneck in 5G networks is data overload, in conjunction with the limited storage and computational power of UEs and BSs. A recently proposed solution is to use distributed structures for processing reasons (Fig. 2-7). In wireless networks, this is mostly achieved via MEC architectures, where cloud, edge and mobile processing cooperate [40]. MEC and ML are inextricably related concepts. MEC, being a distributed approach, uses ML tools in heterogenous topologies (such as 5G and 6G networks) to obtain channel state information (CSI) till the network's edges, in order to define the resource allocation policy in each case. The goal of MEC is to minimize the computation time, by allocating the traffic to different processing units.

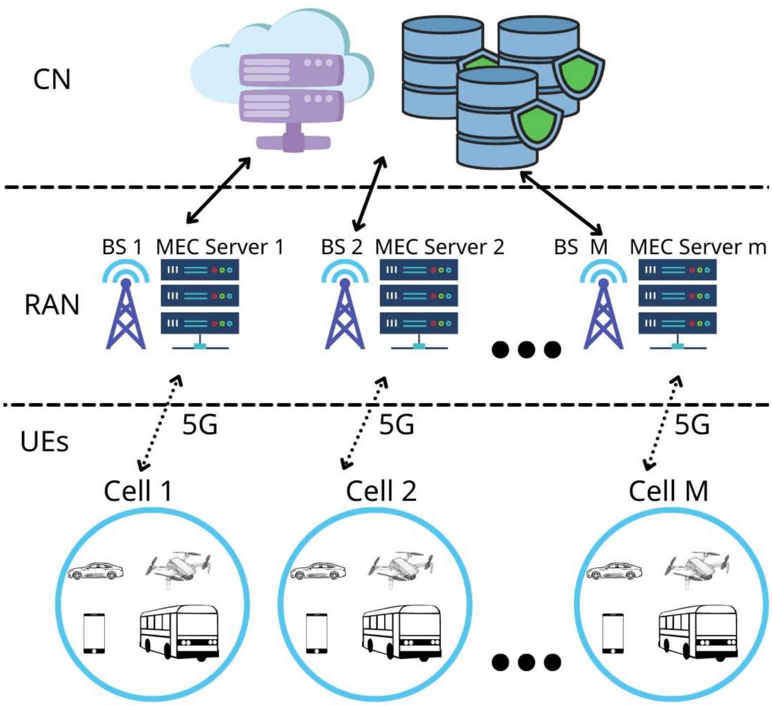


Figure 0-7: MEC in 5G/B5G networks

MEC is primarily based on minimizing computational latency by distributing processing tasks across different processing units. According to Figure 2-7, considering a UE n located in a cell of a 5G/B5G system, a MEC server m installed at the BS which serves UE n, and a computational task j that user n wants to execute with the assistance of m, the total system delay is given by [41], [42]:

$$T_{m,n,j} = {T_{m,n,j}}^{T} + {T_{m,n,j}}^{D} + {T_{m,n,j}}^{E} \quad (4)$$

Where ${T_{m,n,j}}^{T}$ is the time to transmit task j from UE n to serve m, ${T_{m,n,j}}^{D}$ is the computational latency inserted form UE n and ${T_{m,n,j}}^{E}$ is the execution time of task j in server m.

In this strategy, there are three different computational offloading types:

1. ***Local computation***, where all computations are performed at the MEC server installed at the BS, and the UE simply sends data there for task execution. In this case,

${T_{m,n,j}}^{D} = 0$ as all processing is conducted at the MEC intermediary installed at the BS. Therefore, ${T_{m,n,j}}^{T}, {T_{m,n,j}}^{E} \neq 0$.

2. ***Partial offloading***, where the execution of tasks requested by each UE is shared between the MEC server and the UE to some extent. Thus, in this case ${T_{m,n,j}}^{T}, {T_{m,n,j}}^{D}, {T_{m,n,j}}^{E} \neq 0$.
3. ***Complete offloading***, where the execution of tasks requested by each UE is entirely performed on the UE. In this case, ${T_{m,n,j}}^{E} = 0$ as all processing is carried out on the UE. Thus, ${T_{m,n,j}}^{T}, {T_{m,n,j}}^{D} \neq 0$.

2.4.1 Federated Learning

Traditional ML techniques (Supervised, Unsupervised, or even classic distributed learning techniques), which rely on a centralized entity to produce the learning outcome (centralized learning – CL), can phase difficulties in dealing with the computational complexity aspect. For example, most ML models are trained in a central server with lots of processing unit power to produce a global model that will be used by either the network or the end user. These approaches may have a significant number of drawbacks when comes to the efficient use of AI/ML techniques, such as not real-time responses, local data dependency, and security threads (e.g., single point of failure). Thereby, decentralized and distributed ML strategies should be taken into account.

A promising way to tackle these challenges is a specific type of distributed learning technique, introduced in [43] denoted as Federated Learning (FL), which combines MEC and ML. The key characteristic of FL is that edge devices contribute to a global ML model construction, only by transmitting locally trained models' parameters to a central entity, e.g. a centralized server. This means that the training sets of each enrolled edge device are not distributed to the server, maintaining a secure and robust learning framework [44]. FL can also be performed without even sending parameters to the server. In these cases, neighboring devices form a device cluster to exchange parameters for ML models' construction [45]. As it is visible, a significant advantage of FL schemes has to do with their ability to reduce communication overhead and secure communication, as there are no datasets distributed. For all these reasons, FL has gained increasing interest for compute vision tasks [46]

Recently, FL has been proposed as a promising solution in different PHY-related tasks in 5G and 6G networks. Traffic data are continuously generated by UEs, while parameters such as CSI are also present in each UE –BS link. Thus, real-time decision-making can be FL-driven to provide robustness in minimizing the time between data generation and data utilization for these purposes. Thus, FL is useful for convex and non-convex problems in 6G networks', such as interference management, radio RRM, user profiling and grouping, BS -or even relay node (RN)- selection and others.

Fig. 2-8 illustrates an FL framework in the context of new era wireless networks as previously described. Counter to CL methods, where local data (from UEs in 5G/B5G (Beyond 5G) networks) are uploaded to a centralized server, and also counter to classical distributed approaches, where data is uniformly distributed among the edge devices, FL schemes use local data to train a global model, through multiple training iterations across interconnected edge devices (UEs), in order to achieve the desired global accuracy. Then, local updates, generated by each interconnected device, are aggregated to a cloud or a MEC server (in BSs).

In such scenarios, FL targets ML KPIs (accuracy, F1-score, root-mean-square-error (RMSE)) maximization by the application of multiple communication rounds between the server and the edge devices to train and/or update the model with local datasets.

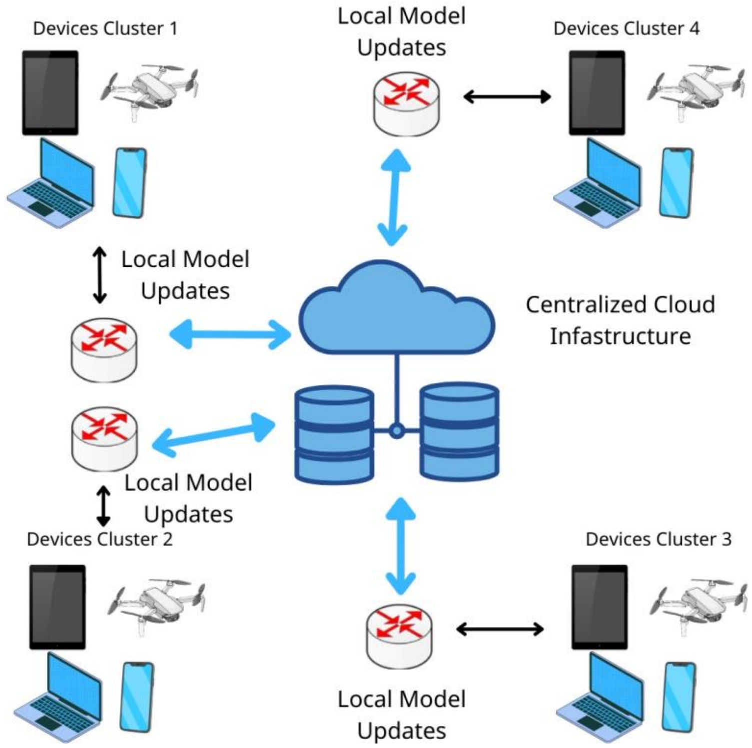


Figure 0-8: FL in 5G/B5G networks

When it comes to FL techniques, where multiple nodes should cooperate to construct a global ML model, the following tree-type classification exists (as also depicted in Fig. 2-9):

- In CL, edge devices send their locally gathered data to a centralized entity for training purposes (see Fig. 2-9a). Thus, the distributed computation is limited to the transmission of the local datasets to the centralized server [47]. The key advantage of CL methods is that a total dataset is formed, which helps towards the maximization of ML KPIs, due to the increased amount of data that are existing [48]. On the other hand, the need for whole datasets transmission to the centralized entity has two basic drawbacks. The first one is related to the increased interference and overhead that is introduced, which, also, affects the total response time, a vital aspect concerning the real-time decision-making nature of 6G communications. The latter is the possible security vulnerabilities and threads that can phase privacy data through transmission.
- In FL, edge devices gather their local data and form a local model, which training is performed at the edges. However, the centralized entity's role is to aggregate the different model's parameters, gathered from the edge devices, and, then, distribute the aggregated parameters or the model updates back to the edge devices (UEs). It is visible that the role of the centralized entity is the flow management of the whole process [48], [49] (Fig. 2-9b). The key advantage of FL, compared to CL, is that the transmission overhead is minimized, due to the fact that only ML models' parameters or updates are transmitted to the centralized entity. However, this comes along with the drawback that ML KPIs performance may decrease because the amount of data in each of the separate distributed models is significantly less [46],[49].

- In hybrid schemes, CL and FL are combined, to produce a more dynamic framework that can be used in practical scenarios. The need for such schemes originates from the imbalanced computation capabilities of different UEs in wireless networks. In fact, there are computationally powerful UEs, such as computer systems, local networks or even servers, but there are, also, non-powerful UEs, such as cell phones or UxVs. In such scenarios, computationally powerful UEs perform FL tasks (active state), while the others not (inactive state) [48], [46], as also depicted in Fig. Fig. 2-9c.

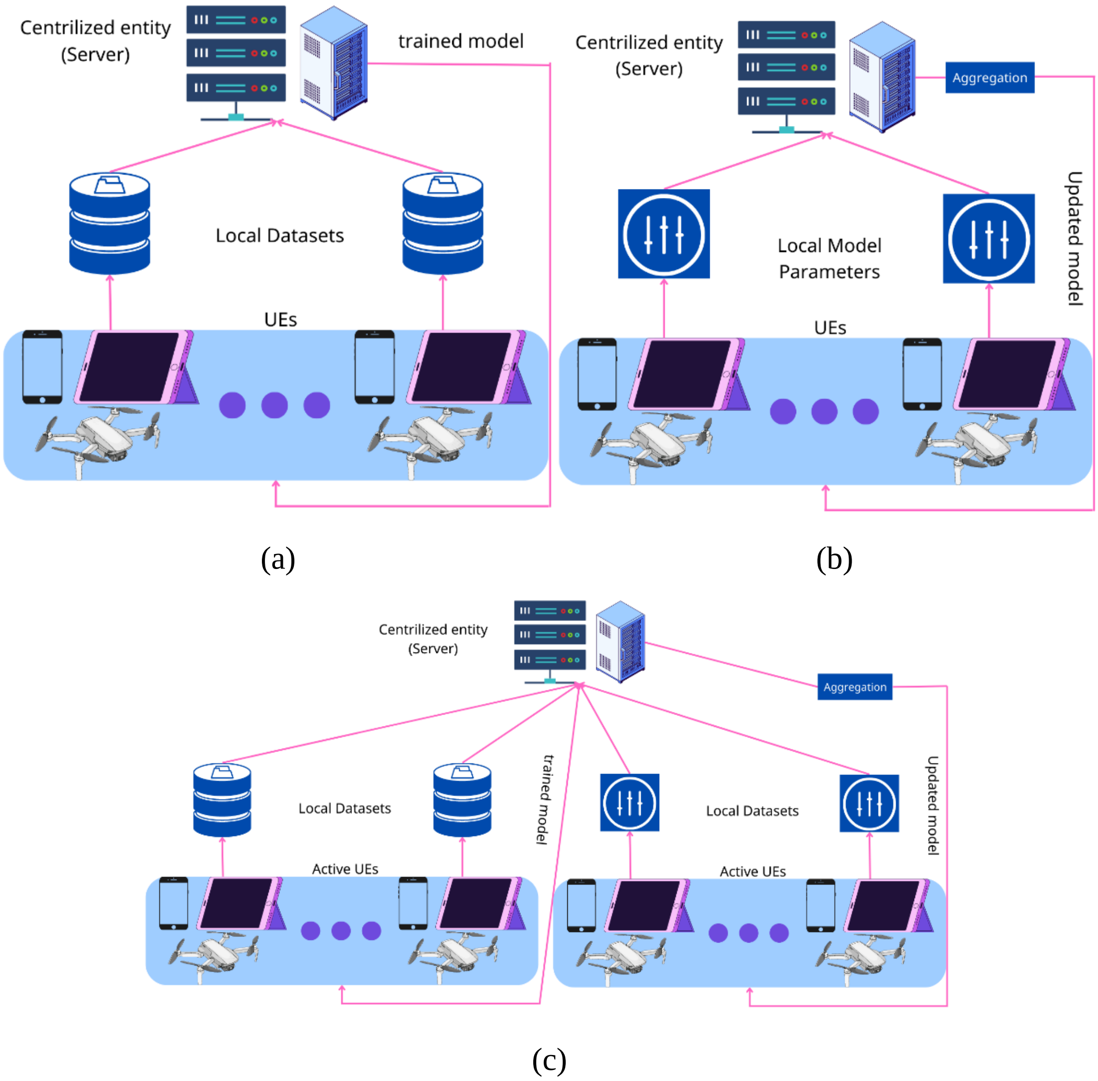


Figure 0-9: (a) CL, (b) FL, (c) Hybrid architectures

Chapter 3: ML-based Radio Resource Management in 5G/B5G Networks

In this chapter the RRM problem in 5G/B5G networks is discussed to highlight the need for fast responses and quick decision-making mechanisms, which are based in ML/DL techniques. To do so the RRM problem is mathematically formulated along with the relevant constrains, based on which this problem should be considered in 5G/B5G networks. Moreover, traditional (non-ML) optimization approaches are presented, while the limitations of such approaches are identified. To overcome those limitations, several ML-enabled schemes for effective RRM in 5G/B5G networks are proposed in next chapters. In this chapter, the relevant literature regarding ML-approaches in 5G/B5G networks' RRM is analyzed. In paragraph 3.1 the emerging role of ML in 5G/B5G is presented. In Paragraph 3.2 the RRM problem is formulated in 5G/B5G networks along with the relevant constrains. Moreover, the traditional optimization techniques that are used for those problems are discussed. Finally, the limitations of the traditional non-ML approaches are derived, witnessing the need for ML-enabled RRM solutions. Paragraph 3.3 presents a literature review over the utilization of different (Supervised, Unsupervised, Reinforcement, Distributed) ML techniques for effective RRM policies definition in 5G/B5G networks. Finally, Paragraph 3.4 presents the outcomes over the state-of-the-art works in ML-based RRM in such networks.

3.1 The emerging role of ML in 5G/B5G

It is already visible from chapter 1 that 5G acts as an integrator for diverse applications and services. To this end, 5G/B5G networks utilize vehicular communications [50], device-to-device (D2D) communications [51], machine-to-machine (M2M) communications [52], MEC [53], cloud computing [54] and internet of things (IoT) [55], in order to meet the needs for eMBB, mMTC and URLLC [56].

More specifically, the authors in [57], [58] summarize the key components and innovations incorporated in 5G networks, as: a) Modern approaches in radio-link management such as open radio access network (O-RAN) and virtual networks, in order to meet the strict criteria of latency, capacity and data traffic in 5G transmission, b) Extended coverage, which includes the installation of multi-nodes and multi-antennas in the network's coverage area, in order to

use multi-hop techniques for fast handovers through service cells and base stations (BSs), c) Service-based network dimensioning, which utilizes the self-generated channel state information (CSI), in order to meet the enhanced URLLC criteria. Cell and BS planning should follow even stricter requirements to support new usage scenarios and applications (smart cities, IoT, emergency alerts). Thus, heuristic approaches, based on data analysis and ML, are proposed in network dimensioning [59] and d) Use of new frequency bands, which includes the extended operating spectrum band and the new spectrum regimes [60].

In addition, 5G and B5G networks extend the deployment of technologies that were introduced in 4G networks and also encapsulate new ones (see also Fig. 3-1). As also presented in Chapter 1, these include massive m-MIMO configurations [61], mmWave transmission [62], network slicing [63], RNs [64] and NOMA [65]. However, the coexistence of these technologies can significantly increase network complexity, due to the insertion of multiple computational levels and hardware needs, thus necessitating the importance of optimal RRM strategies [66]. For example, accurate CSI is required for the effective deployment of m-MIMO architectures and NOMA schemes. This, in turn, increases the overall signaling burden, due to the increased number of pilot signals. Moreover, in typical MIMO configurations, each antenna is connected to a separate radio frequency (RF) chain, thus supporting a fully digital (FD) beamforming approach. However, in an m-MIMO case, this would be prohibitive, as it would significantly increase hardware complexity. Hence, suboptimal techniques are proposed in the literature, based on a hybrid analog-digital beamforming approach [67].

It is, therefore, understood, that a tradeoff between optimal network goals and computational complexity can only be achieved through an efficient RRM. Until now, the allocation decisions were made continuously in each timeslot, based on local network conditions and the data traffic load to be serviced. However, the aforementioned enhanced requirements of 5G networks raise the need for, if not require, a decentralized and intelligent data management system, that can support flexible RRM decisions. In this direction, the utilization of data offered by ML and the features extracted by the corresponding algorithms can effectively contribute to fast RRM responses [68], [69].

Research interest in incorporating ML techniques in 5G/B5G networks has focused mainly on the CN in the past [70]-[72] (indicatively: traffic forecasting [73], [74], network slicing [75], privacy and security [76], etc.). Lately, ML models are introduced in RAN and the development of AI/ML-based RRM algorithms has attracted scientific interest, as well (e.g. [77]-[80].

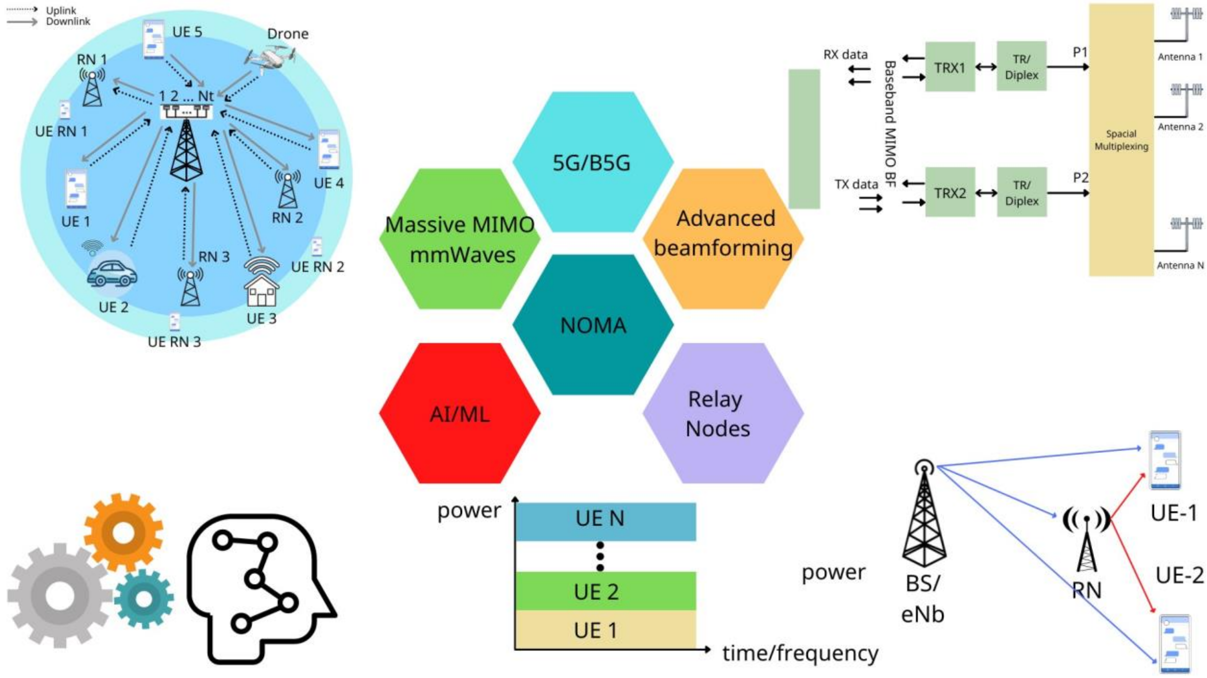


Figure 0-1: 5G/B5G networks enablers

3.2 Radio Resource Management in 5G/B5G System

3.2.1 Problem Formulation

Even though RRM problem's criticality originates from the first steps of wireless and mobile communications, the significance of effectively managing the available radio resources was empowered during the 4G era, when the increase of data rates was accompanied by the high interference levels (especially co-channel). In the 4G, 5G and 6G era, RRM considers not only the allocation of physical resource blocks (PRB's) or subcarriers (typical subcarrier spacing is 600 kHz in frequency range 1 (FR1) of 5G and 2400 kHz in FR2) [60], [81], but also power management, scheduling, traffic control and handover management.

In general, RRM considers two main objectives, that in case can be treated as joint. The first one is power minimization, which is referred to as margin-adaptive (MA), while the latter is network efficiency maximization. In this framework throughput (or rate) maximization (rate adaptive - RA) is mainly considered. MA minimization considers overall and per user minimization of power consumption. Respectively, RA maximization takes into account overall and per user minimum throughput maximization [82]. Both approaches include a plethora of parameters, at cases mutually exclusive, that can significantly increase the complexity of RRM. In fact, in [81], the non-deterministic polynomial-time (NP)-hardness of the resource allocation problem is proved. Consequently, sub-optimal solutions are proposed.

In the 4G-LTE era, when OFDMA techniques were introduced, RRM algorithms mostly considered the maximization of users' throughput, based on QoS requirements, such as the key implementation criterion. The main categorization was the stage at which RRM was performed, considering sectors or BSs, with centralized or decentralized approaches.

An innovative solution was introduced by game theory, where the RRM problem was treated as a game and each user as a player. Techniques such as Nash bargain (NBS), Hungarian NBS and Raiffa bargain (RBS) were the most common ones [83].

In a typical 5G/B5G m-MIMO cellular orientation, the total bandwidth, denoted as W, is divided into a predefined number of L subcarriers, which are allocated to users, according to their demands and overall constraints [84]. The system serves as many users as possible, till all subcarriers are allocated (N users). BSs are equipped with Mt transmitting antennas, while users are equipped with Mr receiving ones. The signal-to-noise-plus-interference-ratio (SNIR) for the n^{th} user ($1 \leq n \leq N$), associated with the l^{th} subcarrier ($1 \leq l \leq L$) for a specific channel realization and assuming independently transmitted streams among different users, is defined as follows [85]:

$$SNIR_{n,l} = \frac{G_{n,n,l}}{\boldsymbol{r}_{n,l}^{H} r_{n,l} I_0 + \sum_{m \neq n, l \epsilon S_m} G_{n,m,l}} \quad (5)$$

where $G_{n,m,l} = p_{n,l} \boldsymbol{t}_{m,l}^{H} \boldsymbol{H}_{n,\sec(m),l}^{H} \boldsymbol{r}_{n,l}^{H} \boldsymbol{r}_{n,l} \boldsymbol{H}_{n,\sec(m),l} \boldsymbol{t}_{m,l}$, $\boldsymbol{H}_{n,\sec(m),l}$ represents the $Mr \times Mt$ channel matrix for the l^{th} subcarrier of the n^{th} user relevant to its serving sector, $\boldsymbol{t}_{n,l}$ is the $Mt \times 1$ transmission vector, assuming diversity combining transmission mode, $\boldsymbol{r}_{n,l}$ is the Maximal Ratio Combing multiplying vector and $p_{n,l}$ denotes the transmission power allocated to the l^{th} subcarrier of the n^{th} user. Moreover, the set S_n indicates the subcarriers allocated to the n^{th} user and I_0 is the thermal noise level. Finally, $\boldsymbol{A}^H$ denotes the conjugate transpose of matrix **A**. Thus, the achievable data rate on the l^{th} subcarrier is $r_{n,l} = W * \log_2(SNIR_{n,l})$ [86], and the corresponding aggregate rate for the n^{th} user is $R_n = \sum_{s \in S_n}^{N} r_{n,s}$. Then, the total throughput is given by:

$$R = \sum_{n=1}^{N} R_n \quad (6)$$

In most of the state-of-the-art RRM works, the target is to maximize EE, SE, Jain's fairness index (J) and, at the same time, minimize blocking probability. EE and SE are given by:

$$EE = \frac{R}{\sum_{n=1}^{N} \sum_{s \in S_n} p_{n,s}} \quad (7)$$

$$SE = \frac{R}{W} \quad (8)$$

$$J = \frac{\left(\sum_{n=1}^{N} \sum_{s \in S_n} r_{n,s}\right)^2}{N * \sum_{n=1}^{N} \sum_{s \in S_n} r_{n,s}^2} \quad (8)$$

Finally, blocking probability (BP) is defined as the ratio of rejected users to the total number of used that tried to access the network.

The aforementioned optimization problem is subject to the following system constraints:

- $\sum_{s \in S_n} p_{n,l} \leq p_{max}$, where p_{max} denotes the maximum power limit per user.
- $p_{n,l} \geq 0, 1 \leq n \leq N, 1 \leq l \leq L$, which demonstrates the non-negative power constrain of the transmit power on each subchannel.
- $SNIR_{n,l} \leq SNIR_{thr}$, which sets the minimum SNIR threshold for acceptable QoS.
- $N_{l,t} \leq N_{thr}, 1 \leq l \leq L, 1 \leq t \leq T$, where $N_{l,t}$ is the number of users, grouped in the l^{thr} subcarrier over time slot t, and N_{thr} is its upper threshold, in the case of NOMA transmission [87].

3.2.2 Traditional RRM approaches

As already mentioned, the RRM problem belongs to the category of NP-Hard problems, making it extremely difficult to find the optimal solution using conventional approaches. However, machine learning is proposed as a more efficient solution compared to existing methods. Before delving into the reasons why ML approaches are considered suitable for addressing the 5G/B5G RRM problem, this sub-paragraph presents a summary of significant up-to-date approaches, which tackle the RRM multi-objective problem and do not make use of ML techniques (defined as “non-ML” throughout the rest of this thesis). The relevant literature in this sub-section is representative with respect to various network metrics, such as throughput, QoS, interference mitigation.

In [88], a resource allocation scheme is proposed, where target SNIR values are accompanied by the minimization of power consumption. In the same context, in [89], the available spectrum is shared between macro and micro cells to maximize the number of users and achieve the SNIR requirements of each micro or macro cell user. In [90], a different approach

is considered, where the distance-based resource allocation scheme is replaced by a model, based on priority classes of the mobile devices in mobile type communications (MTC) networks. This approach, apart from SNIR, considers latency, total induced delay and pending number of MTC devices, as well, for priority classes construction.

A key aspect in resource management policies in 5G networks is the harmonization with both QoS and QoE requirements. While QoS defines the user's satisfaction in a strict technical way, QoE reflects the overall user's happiness or frustration. The relationship between QoS and QoE is presented in Fig. 3-2. According to [91], there are two main (and one upcoming) ways to achieve the optimal joint satisfaction of QoS and QoE. The first one refers to the network's architecture and is the use of self-organized networks (SONs).

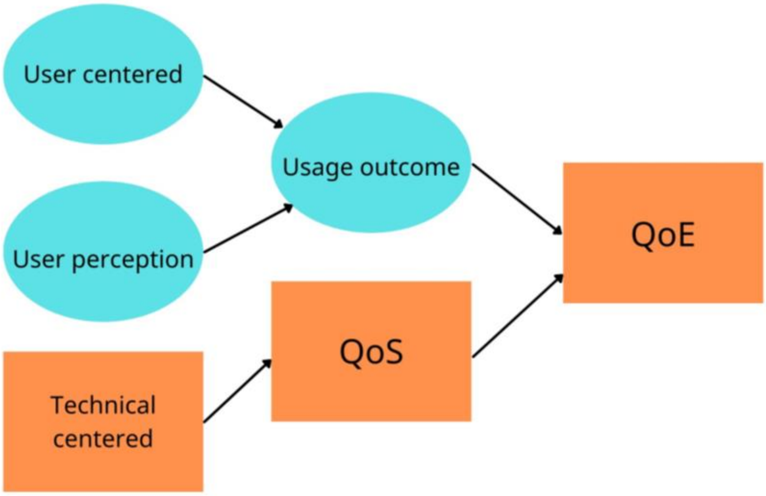


Figure 0-2: QoS and QoE

The other one refers to the efficient tradeoff between packet loss, latency, traffic data (objective parameters) and mean opinion score (MOS), that should always exist. Last but not

least, the integration of ML techniques in RRM, specifically NNs, which use data-driven (CSI-driven) techniques, in order to solve the optimization problem, can contribute in the direction of joint QoS and QoE requirements' satisfaction.

In the existing literature, the significance of both QoS and QoE requirements' satisfaction is highlighted. For example, the authors in [92] consider the resource allocation problem in M2M 5G 3GPP cellular systems. An optimal radio resource allocation method in LTE and beyond cellular networks is developed, based on adaptive selection of channel bandwidth, depending on the QoS requirements and priority traffic aggregation. Furthermore, a novel simulator is proposed, focusing on the joint impact ofM2Mand human-to-human (H2H) traffic in 5G/B5G networks. In order to ensure the satisfaction of QoS requirements, the proposed simulator automates RRM algorithms for both the M2M and H2H traffic. The simulations and results indicate that the proposed framework improves the radio resource management policies' application by 13%, concerning the LTE frame formation process.

Wang *et al.* [93] use QoE utility function for spectrum and power allocation in macro and pico-cell HetNets. For the subcarrier allocation method, they construct a weighted bipartite graph and revise Kuhn-Munkres algorithm to obtain perfect matching. For power allocation, they use the first order derivative of the network utility function, achieving the nearly-optimal levels of power minimization. However, increasing the cell size results in QoE deterioration. In the same framework of using QoE utility function, the authors in [94] consider the joint subcarrier, assignment and power allocation problem. The proposed approach is based on the

decomposition of the general problem into two sub-problems: the BS selection and subcarrier allocation sub-problem and the power allocation sub-problem. A genetic algorithm for the first problem and an artificial bee colony (ABC) algorithm for the second one are proposed. The simulation results indicate that the proposed power allocation scheme reaches optimal solution levels quickly, while MOS increases for increasing number of active UEs or available subcarriers.

In 5G HetNets, interference can have a critical impact on the selection of the appropriate RRM strategy. There are three types of interference. The first one is cross-tier interference, which occurs between users in different tiers, such as between macrocells and fempto-cells (FCs). On the other hand, co-tier interference is experienced by users within the same network tier [95]. Finally, inter-cell interference occurs mainly at the cell edges, where a user can receive signals from multiple BSs/RNs. The authors in [96] consider a 3-tier HetNet and propose a joint interference and resource allocation strategy. The examined use cases enhance D2D communications in macro and small cells topology. The joint sub-band and resource block (RB) allocation problem is solved, with respect to the QoS levels and D2D interference minimization. The proposed scheme alleviates significantly co-tier and cross-tier interference, compared to traditional techniques. On the other hand, the proposed algorithm introduces delays that could cause difficulties in the deployment of the scheme in real-world scenarios. In the same context, authors in [97] examine the influence of intercell interference in the design of effective RRM strategies. More specifically, they formulated an EE maximization RRM problem for a downlink OFDMA HetNet, and solved it via a two-step generic algorithm. The firrst step concerned subcarrier allocation under SE requirements, while the latter power management. Simulation results indicated that a tradeoff between EE and total achieved throughput should exist, proposing small cell deployment as a way to simultaneously improve both factors.

Xu *et al.* propose in [98] a resource allocation scheme to maximize the system throughput, by considering cross-tier and co-tier interference for macrocell users, as well as the transmission power in HetNets. The proposed scheme uses a nonlinear programming formula, solved by distributed Lagrange dual methods. This method results in interference limitation for the users spread in the topology. However, the adopted approach involves many iterations, thus leading to increased overall delays.

In [99], a joint RRM problem is investigated and solved sequentially in an mmWave environment. The first one is related to beam selection (beamforming), while the second one to power allocation. These problems are formulated into mixed integer nonlinear programming (MINLP) problems. The authors solve the first problem using cooperative games theory. In this way, optimal beam allocation is achieved and served as input to the second problem, where the power allocation scheme is determined, employing Lagrange duality and an iterative water-filling algorithm. According to the presented results, there are significant throughput improvements, compared to classic RRM schemes. On the other hand,

computational complexity is extremely increased, reaching almost prohibitive levels.

In [100], a similar joint routing and resource allocation problem is investigated, considering multi-tier analysis approach for mmWave systems. Resource allocation concerns the physical layer, while path selection concerns the network layer. A stochastic algorithm is used for RRM and a linear programming one for the path selection. The EE and the overall system throughput are significantly improved, compared to state-of-the-art algorithms. However, a lot of delay factors are inserted, due to the adopted cross-layer approach. Therefore, this scheme might be inappropriate, when dealing with URLLC demands in emergency situations.

Another significant metric that originates from throughput is SE, which is the "clear" information that can be transmitted over a specific spectrum area in a wireless environment.

In this context, the authors in [101] propose a resource allocation system, based on SE requirements. They make use of a hybrid-clustering game algorithm, that mitigates co-tier and cross-tier interferences. The clustering problem is solved using graph theory, and more specifically a maximum K-cut algorithm in the interference graph of the topology. Then, inside each cluster, resources are allocated to users, implementing an auction game mechanism algorithm. According to the presented results, there are significant improvements,

compared to state-of-the art approaches, in terms of SE and throughput. However, we should mention that, by the above scheme, both macro and micro-cell users are treated as one entity. In this case, the QoS and QoE metrics are not taken into consideration.

In ultra-dense modern era networks, power consumption becomes a key issue. Thus, the metric of EE is used to measure the power consumption in the topology [102]. In this context, a complex scheme is proposed in [103], that jointly maximizes EE and SE. There are three different components in the proposed scheme. The first one is a system to balance the load between the BS of service and other BSs in the topology, along with handover management. The second one aims to manage inter and intra-cell interference and frequency reuse. Finally, the third one applies a proportional fairness (PF) allocation policy to guarantee fairness among

users. A binary search algorithm implements the resource allocation, maximizing EE and SE. Therefore, this approach is beneficiary for commercial use cases, due to the fast decision-making mechanism, leading to optimal solutions. However, the fully centralized nature of the algorithm might increase overhead, due to the increased round-trip time.

Another key issue in future networks is the limitation of usable resources to tackle the spectrum scarcity problem. Dynamic spectrum sharing is proposed as a novel method for the cooperation between 4G-LTE and 5G technologies, as different spectrum resources can be allocated, based on users demands, establishing improved SE levels and spectrum utilization. The authors in [104] proposed a dual bargaining game model to solve the spectrum sharing problem guarantee effective real-time collaboration between LTE and 5G systems. Results indicated that this scheme improves total throughput and service failure by 5-10% compared to traditional approaches.

Furthermore, the increased number of traffic load from mobile devices, which causes the densification of wireless networks, empowered the deployment of revolutionary centralized alternatives of the classical cellular architectures, such as Cloud RAN (CRAN) and O-RAN. In CRAN architectures the baseband processing unit (BBU) is moved from the BSs onto a centralized cloud/edge BBU pool, while O-RAN indents to provide open air interfaces and separate user and control plane functions. The authors in [105] proposed a two-stage optimization algorithm for the joint secondary user selection, spectrum allocation and time scheduling problem of downlink transmission in CRAN. Results indicated that improved data rates, time scheduling and prioritization for big data transmissions can be achieved using the above scheme.

Concerning O-RAN, the authors in [106] implemented a mixed-integer linear algorithm to solve the joint distributed unit and subcarrier allocation problem, with respect to energy and latency minimization for delay-sensitive communications. Results indicate that the proposed approach consumes less energy under a larger network size, compared to a disjoined scheme.

3.2.3 Limitations of non-ML approaches

In the previous paragraph, significant non-ML approaches, concerning RRM in 5G and B5G networks, are presented, where various sub-optimal solutions are proposed, due to the multiparameter nature of the problem. However, focusing on the outcomes and results of those research efforts, several limitations can be witnessed. In most cases of LTE and early 5G networks [92], [94], [95], [99], the enactment of the RRM policy was based on perfect knowledge of specific parameters, such as the instantaneous CSI and QoS requirements of the active users. Thus, the optimal allocation problem, described in the above paragraphs, is solved through optimization procedures. However, it is also apparent from the problem formulation that, in practical wireless orientations, multiple difficulties may arise, thus making resource allocation a multidimensional problem. More specifically:

- Most of the non-ML techniques provide solutions which are not universal. Optimal solutions are highly correlated to the current circumstances in each network's topology, user demands and qualifications. Thus, RRM, in general, is a problem characterized by non-conventionality [106].
- The provided solutions may not be obtainable in real time. HetNets and IoT networks have high levels of time variability. An optimal solution in a time slot or interval is not by default optimal for the next time unit [98], [99].
- The wireless channel in 5G and B5G networks is defined by an extremely high propagation scheme, with users characterized by random or partially unknown mobility patterns. In these scenarios, the mathematical formulation of the problem is arduous and, in general, not easily defined [102].

According to these considerations, more efficient RRM solutions should be implemented in both computational and performance perspective. In this framework, ML-based resource allocation algorithms are proposed in the literature, as an efficient way to deal with the abovementioned limitations. In the next paragraph, the state of research in the field of ML-enabled RRM in 5G/B5G networks is presented.

3.3 Existing ML Literature Review

In this paragraph, the related research concerning the use of AI/ML in RRM is presented, classified in terms of type of learning and architecture (centralized vs distributed). The performance of the used models is also discussed, and conclusions are drawn upon them.

3.3.1 Supervised Learning in 5G/B5G RRM

The authors in [107] consider a SON topology. A 5G network simulator is proposed, along with a pathloss model, using metrics, such as SNIR and throughput (LTE KPIs) in order to deal with the problem of dynamic frequency and bandwidth allocation in these topologies. The system is tested in several frequencies and bandwidths. In order to set the RRM policy and predict the KPIs, several ML methods, such as bagging trees, boosted trees, SVMs and linear regressors are evaluated. Bagging tree prediction witnesses the best overall performance. The main feature of this method is that it uses bootstrap sampling in deep decision trees, in order to reduce the variance of the model and classify data correctly to predict the network's KPIs. According to the derived results, the decision tree learning-based method reaches 95% of optimal network's performance. Finally, the authors highlight the necessity for a joint consideration of networks' KPIs and ML performance metrics.

Working also on KPIs prediction, the authors in [108] designed a predictive model for the overall users' demand. Then, they use an ML-based supervised classifier to allocate the network resources dynamically (Network Resource Allocator). The employed metrics are bandwidth, latency, jitter times, QoS and QoE. The decision process for data traffic and allocated subcarriers is defined by QoS and QoE. The learning procedure is based on previously gathered experience from offline measurements. Thus, the proposed Network Resource Allocator empowers an automated flexible and elastic network. The models are employed in the network's controller in order to change the network topology for better traffic management by removing the unused parts of the network to release its unused resources (i.e., subcarriers, unused links, etc.).

In m-MIMO systems, hundreds of antennas are used for detection, resources' allocation and channel estimation (via channel coefficient matrix). In [109], an SVM scheme is proposed for the estimation of the Gaussian channel's noise level and pathloss prediction in urban outdoor environments. The general form of the problem has *t* transmitting MIMO antennas and *r* receiving ones. The model predicts the channel noise statistics, according to which the allocation and multi-tier QoS scheme will act for each independent user or users' category. Three kernel techniques are investigated (Polynomial, Gaussian and Laplacian) and compared to the Okumura-Hatta pathloss model and an ML-based ANN one. Laplacian SVM witnesses the best performance, in respect to both pathloss prediction and computational complexity. The overall satisfactory performance of the SVM approach is due to the use of multi-dimensional representations in feature extraction, leading, thus, to reduced training time and increased capacity. ANNs' performance is similar to SVMs' approach, needing though longer training times, as multiple initializations are requested.

Considering DL approaches, Liu propose in [110] an ANN algorithm for channel learning, to mine undiscovered channel information data from a 5G network. They use location features and CSI and they produce channel samples from 5G simulators, that are latter used as training data for the model. The channel ANN estimation algorithm calculates unseen aspects of the channel approximation and resource allocation scheme. The prediction accuracy improves, compared to traditional *k-NN* classifiers. It remains, though, limited to a level of 75%, but could be further increased by approximately 3%, if geographical information is used in the dataset.

Zhang *et al.* [111] build a deep NN (DNN)-based framework for user, subchannel and power control in NOMA mmWave networks. The solution of the user association problem is given by the Lagrange dual decomposition. The subchannel and PRB allocation is given by a semi-supervised learning algorithm, while the power allocation is given by a DNN model. The use of the described joint ML-based component (for user, subcarrier and power control) delimits the entire decision-making policy in terms of RRM. According to the presented results, the EE of the system is significantly improved, while the resource allocation reaches optimal levels (98% accuracy).

Guerra-Gómez *et al.* [112] propose a dynamic resource management scheme, based on the prediction of the total system's capacity. They use three different ML algorithms: SVM, DNN, and LSTM. According to the presented results, the scheme can perfectly reduce the underutilized resources; however, QoS levels are not optimized. Therefore, the authors propose two novel strategies. The first one considers data pre-filtering and results in an additional 2% minimization of unallocated resources. The latter one considers error shifting

and leads to an additional 3% reduction in unallocated resources. However, the achieved QoS levels form a barrier in this approach.

The authors in [113] consider the problem of optimal and automatic BS selection in LTE and 5G environments. They propose two ML-based classification solutions to satisfy QoS requirements; the _rst one uses SVMs and the second one Random Forest. Both approaches are compared to a non-ML BS selection approach. The results indicate that the ML-based BS selections can improve throughput and decrease outage probability and delay. Specifically for a 50-user topology, ML approaches achieve 23.21% higher throughput levels, 70% lower packet loss ratio and 48% lower delays compared with a non-ML approach.

In the same framework, Butt *et al.* [114] investigate the UE positioning problem in 5G networks. The authors compare a decision tree classi_er with two DNN solutions. The first one uses training data from the service cell and overperforms in terms of accuracy, while the second one uses transformed data from the cell and its neighboring ones. In general, the DNN solutions witness an overall near-optimal performance, in terms of accurate positioning of UEs. In fact, the 2-hidden layer DNN witnessed a positioning error in the range of 1-1.5 m, after appropriate feature selection.

3.3.2 Unsupervised Learning in 5G/B5G RRM

Song *et al.* [115] produce a realistic 5G V2V networks' simulator, with the presence of RNs.A*k-Means* clustering algorithm is responsible for implementing BS or RN selection, user allocation and serving policy. User positioning and RN distribution in the topology are performed via ML, in a way that the serving device, BS or RN, is optimally selected. However, the model calculates every 2D distance from the observation point (in that case UE) to the borders of each cluster and not to the cluster center. Thus, the overall communication environment parameters are not taken into consideration. Moreover, since the proposed *k-NN* algorithm is a generic unsupervised ML method for clustering, its performance can be affected, if UEs have a complex spatial distribution or clustering is performed in different topologies. However, the authors intend to further improve and configure the algorithm, to define a more efficient selection strategy.

The authors in [116] propose a data-based resource allocation scheme, where an ML technique of affinity propagation is used. In general, this approach uses graph theory to perform clustering. The basic advantage of the proposed algorithm is that it does not require the number of the clusters as input. In this way, knowledge and behavior extraction can be made even under complex scenarios. The authors conclude that the data-driven nature of the RRM policy improvs both system's EE and throughput, although, in some cases, the QoS levels are not the desired ones.

Wang *et al.* propose in [117] an asynchronous resource allocation scheme, based on aggregation graph NNs (Agg-GNN). In this approach, every BS or RN aggregates information from its active neighbors with a certain delay. Thus, both the underlying network structure and the system's asynchrony are incorporated. According to the presented results, this approach outperforms heuristic ones, in terms of the total system's capacity. The presented simulations, though, used only a small number of active UEs in the topology. Probably, in more complex environments, GNNs' training time might increase, and, thus, performance might deteriorate.

In [118], the authors propose an integrated scheme for resource management in NOMA environments. The first stage of the algorithm refers to the users' grouping and subcarrier allocation, while the latter one to the power control. UEs are grouped via the *k-Means* method, while subcarrier allocation and cluster definition are calculated using the F-test method. Power assignment is performed for the allocated subcarriers, by formulating a convex optimization problem. The presented results indicate that the proposed approach reduces electromagnetic exposure and increases the total served users. Although in this approach single antenna configurations are used, both in the BSs and the UEs, the authors are aiming to extend their work to MIMO systems.

3.3.3 Reinforcement Learning in 5G/B5G RRM

Alnwaimi *et al.* used RL in [119] to increase spectrum accessibility in FCs. The proposed scheme identities the available spectrum opportunities; then, it selects subchannels, so that they operate avoiding intra/inter-tier interference and meet certain QoS requirements. A key aspect of this approach is that the considered method reaches optimal levels, in terms of sub-carrier allocation, even in tiny cell topologies. The basic contribution of this approach is the reduced convergence time and the fast-decision-making procedure. However, these come at the cost of reduced accuracy which is now limited to 75%.

In [120], an RL-based algorithm chooses the frequency channel and determines whether to change its location in the presence of jamming and strong interference. A Q-learning algorithm determines the above decision, while a deep CNN accelerates the channel feature extraction. The scheme operates extremely well for huge channel numbers, in terms of interference mitigation, and increases SNR levels compared to a simple Q-learning system (without CNN).

The authors in [121] propose a deep RL framework for power control in 5G HetNets. The problem is formulated aiming to minimize the difference between the mobile users' allocated and requested throughput, by adjusting the transmitted power of the macro-BS or RN. According to the presented results, the proposed approach reaches optimal levels of users' satisfaction, based on achieved throughput compared to traditional water-filling [122] and weighted minimum mean squared error (WMMSE) approaches [123]. However, as expected, the difference between user demands and allocated throughput is increased, as the user requirements do so.

The authors in [124] propose a distributed multi-agent deep RL (MARL) framework for joint user and power allocation, in a dense wireless network. The data are generated by real measurements and backhaul delays. The results, via simulations in dense wireless networks, indicate that the scheme achieves a tradeoff between sum-rate and 5th percentile rate, similar to centralized scheduling algorithms. The authors intend to verify the performance of the RL scheme in realworld scenarios in the future.

The authors in [32] use QoS as the basic metric in an ML-based resource allocation scheme. An RL (Q-learning) algorithm is used for the radio access technology (RAT), while the actual RRM is developed, employing the Montecarlo tree search (MCTS)-based Q-learning algorithm. The authors prove that optimization is achieved after a reasonable number of searches and that it outperforms other scheduling methods, with respect to the system throughput and resource utilization. However, the computational complexity is increased, due to the exhaustive use of the MCTS method. This could be a disadvantage in real case scenarios.

Moreover, RL methods are utilized [125] in order to minimize the total transmission power in HetNets, while jointly satisfying the bit rate requirements of different UEs. Every UE can be connected to one of the available BSs or to another UE, which acts as an RN. The authors use Q-learning in the decision-making procedure. The proposed algorithm reaches optimal levels, in terms of the resource allocation. In addition, the decentralized nature of the algorithm, constitutes a very promising approach with future extensions, as it uses specific UEs as BS/RNs.

RL methods have been also used in 5G satellite communications to efficiently perform RRM related tasks. More specifically, the authors in [126] propose an intelligent RL wireless channel allocation algorithm for 5G m-MIMO High Amplitude Platform Station (HAPS) networks, based on Q-learning and back-propagation NNs. The entire network is trained using the Q-learning model, while CSI information is collected in the platform, through real-time agent interaction with the environment, and thus, updating the Q-algorithm using a back-propagation NN. Results indicated that, even if the number of agents is very high, the channel allocation accuracy levels remain high (over 75%).

3.3.4 Distributed technologies in 5G/B5G RRM

Focusing on MEC technologies in RRM, the authors in [42] present the state-of-the-art on the employment of MEC networks, focusing on architecture, cashing, computation and use of ML-based schemes. In general, caching refers to the temporary storage of content (CSI in RRM-related tasks) in centralized or decentralized databases, for future access. The reasoning behind those storages is that an instance (i.e., a D2D communication in RRM), that has occurred once, is very likely to occur again in the future. In MEC systems, these techniques are commonly used for decision making and allocation of available resources. For example, the authors in [127] reach a 10 -11% lower latency and improvements in QoE, compared to non-caching schemes. The authors in [128] propose an efficient content caching policy for edge using dynamic ML predictions. The proposed Long-Short-term Memory approach provided 30% higher caching ratio, than conventional approaches.

MEC and ML are combined in complex optimization problems, as well. In this context, resource allocation, beamforming and caching issues can be jointly encountered. Related works in this field use DL models, such as ANNs, for accurate computations. Such efforts are described in [129] and [130], considering decentralized hybrid beamforming in 5G next generation node BSs (gNodeBs). The proposed novel techniques (CNN frameworks in both [129] and [130]) outperformed state-of-the-art optimization-based and greedy-based algorithms, both in terms of SE and computational complexity.

A key characteristic of RRM-related tasks is that active UEs or edge devices have different processing power, antenna characteristics and mobility patterns, leading, thus, to heterogeneity in local datasets. More specifically, the data generated in each UE contain different labels and/or features and are not of the same volume. This is called non-independent and identical distribution (non-IID) in the generated data [130]. Therefore, the need for the distributed training of ML algorithms in different UE or network devices is a key technique in 5G, but especially in B5G networks. Thus, the purpose of implementing FL schemes in RRM (i.e., resource allocation, latency minimization) is, also, to address the aforementioned heterogeneity and, in that way, improve the accuracy of the global model [131].

In 5G networks the main PHY layer (RRM) domains where FL schemes are employed consider user allocation, subcarrier or Physical Resource Block (PRB) allocation, power management, BS or RN placement, and selection. However, towards 6G networks deployment FL is combined, also, with other newcoming technologies such as NOMA, CF mMIMO and RIS. In the rest of this subchapter the recent approaches in literature are presenting concerning the application of FL schemes in the aforementioned cases.

RRM

Authors in [131] propose a UE scheduling method in an FL-assisted wireless network, based on the joint quality of channel and learning optimization. When wireless resources are limited, this method improves the overall training time, compared to traditional ones. However, the model's accuracy decreases in an environment with powerful resources, due to data overload.

Authors in [132] consider the problem of joint power and resource allocation for vehicular URLLC communications. The goal is the minimization of the overall system's power consumption subject to high reliability in terms of probabilistic queuing delays. First of all, an extreme-value theory approach is introduced to define the threshold-based reliability measure to detect extreme events to vehicles' queue lengths. A novel FL-based approach is proposed to detect these extreme events, assuming they are independently and identically distributed over different vehicular users. Afterwards, the communication delays detected in the FL scheme over wireless links, are used to define the power management and subcarrier allocation policies for each user. The performance evaluation, indicated that the proposed FL-based model estimates the extreme events presence in vehicle users' queues with the same accuracy as a centralized scheme. Moreover, the data exchange amount is reduced by 79%, while the vehicular users' ques length is reduced by up to 60%. Overall system's average power consumption is, also, reduced compared to a centralized state-of-the-art approach.

On the same framework, authors in [133] proposed an FL-based decentralized joint subcarrier allocation and power control scheme in vehicular networks to ensure string stability in a platoon of autonomous vehicle users. The optimization problem of joint subcarrier allocation and power management is studied subject to both string stability and link availability between different vehicular users. Two schemes are proposed for this problem. The first one considers a centralized BS-governed approach where BSs a priori know the large-scale fading parameters of the vehicular links. The second one, considers an FL-based Multi-Agent Reinforcement Learning (MARL) algorithm, where each vehicle incorporated a distributed agent, which tries to define the optimal policy to maximize the expected reward (power consumption minimization). The last step for its agent is to communicate with the CPU in order to compare the local performance to the global one based on the total achievable capacity. Performance evaluation indicated that both approaches outperformed a random allocation scheme concerning the achieved data rate. However, the distributed MARL outperforms the centralized one concerning the same KPI.

Authors in [134] consider the problem of user scheduling over resource-constrained 6G channels. The authors are pointing out that the uplink scheduling of different devices where FL processes are performed is a problem of interest. A novel approach is proposed for uplink user scheduling based on EE and importance-awareness. In each devise unsupervised graph representation learning tasks are performed. The key novelty of this approach is that an importance bias is inserted in the scheduling process, which does not require the collection of training feedback from client users, unlike state-of-the-art approaches. Performance evaluation indicated that ML tasks' accuracy can be improved by up to 10%. Moreover, EE can be also improved by approximately 17 times compared to the state-of-the-art approach.

In [135] QoS is considered as the most significant KPI in 5G/6G communication networks. However, QoS service requirements rely heavily on user mobility and networks density. Considering vehicular communications, even stricter QoS requirements should be met in real-time scenarios. To address the problem of non-convexity of existing optimization techniques, the authors propose a data-aided federated DRL algorithm for resource allocation in 5G/6G vehicle communication networks. Performance evaluation indicated that an FL DRL scheme can optimize the probability to achieve the requested QoS for each vehicular user of the topology. Moreover, EE and spectral efficiency (SE) levels can be also increased compared to CL approaches.

Concerning device-to-device (D2D) communications, authors in [136] proposed a framework for user device selection to take part in the learning process, as a lot of UEs don't have the computational power to perform FL tasks. Hence, the authors propose a FL framework (based on the matching theory incentive mechanism) to select the devices that will take part in the learning process, aiming to minimize convergence time and to maximize reward. Moreover, parameters such as energy consumption are, also, taken into consideration. In each device, an echo-state-network is running to forecast channel conditions in a reliable manner. Performance evaluation indicated that the convergence time and energy consumption of the proposed FL framework are far better than conventional approaches. In fact, energy consumption can be improved by ~10 Joules, while global FL delay can be reduced by ~20 ms. Moreover, ML models' accuracy is also improved (~96% compared to ~89%). Thus, such approaches are declared as applicable for potential usage in 6G networks. A similar approach is presented in [44], concerning both user selection and resource allocation to minimize the FL loss function. The numerical results indicated that identification accuracy can be improved from ~1% to ~4% compared to a random RRM algorithm, a state-of-the-art FL one and an optimization algorithm that minimizes the overall system's error rate.

Finally, authors in [137] address the problem of energy consumption in FL-based 6G orientations, as the resource-constrained nature of a variety of edge devices bring up a limitation to efficient learning. In general, the data in wireless networks are characterized as non-identically and independently distributed (non-IID), leading to the need for various global updates rounds until decision-making. As a sequence, the authors propose a generic multi-flow relay learning framework algorithm, FedRelay, where relay-assisted local updates are performed in the training phase of the global model. There, a cooperative communication decentralized relay selection protocol is also proposed. The global optimization is performed subject to energy consumption minimization for both each local update and global model. However, computation frequency is considered, also, to reduce training overhead. Performance evaluation indicated that FL-assisted relay selection led to a 5-time reduction in energy consumption compared to state-of-the-art federated learning approaches. Moreover, global test set accuracy is similar to state-of-the-art ones.

NOMA

The aspects of FL and MEC orientations for NOMA-aided wireless communication are, firstly introduced in [45]. Authors propose a framework for terrestrial networks, where simultaneous computation offloading enhanced networks' flexibility. In this way, connectivity is highly reliable, while transmission latency and energy consumption are significantly reduced. FL fundamentals are, also, presented along with several implementation techniques to improve or maintain QoS levels. The authors declare that the cooperation between FL and RL is of high interest for RRM-related tasks. Thus, motivations, challenges, and representative results are presented, focusing on key technical challenges and open research issues of the proposed frameworks.

Authors in [138] investigated the RRM problem in NOMA-based systems, focusing, also, on the device clustering in these networks, based on the required service demands. Two allocation schemes are proposed by the authors. In the first the BS allocates users/devices to clusters based on current CSI and transmit power, to ensure interference mitigation in uplink and downlink. The key characteristic of this approach is the low overall complexity and communication overhead. In the second approach, an FL-based scheme is proposed based on a traffic estimation model, aiming to improve the system's capacity. Thus, BSs, taking into account both traffic prediction and power demands to allocate devices to clusters. Finally, a synchronization method is proposed to synchronize transmissions of the different devices. Performance evaluation indicated that the system's capacity can be increased by ~20 times compared to on OFDMA scheme, while achieved throughput and packet losses are at similar levels.

Concerning, also, RNs, authors in [139] proposed an FL-based RRM scheme for RN-assisted 6G IoT communication networks, where energy consumption reduction is of primary interest. Moreover, the minimization of the total training and transmission time is, also, of interest. Thus, a joint relay scheduling, transmit power allocation, and frequency allocation optimization problem is formulated. A near-optimal performance and low computational complexity are achieved using a graph-theory approach. Performance evaluation depicted that the proposed scheme achieves 6, 4, and 2 times lower energy consumption, respectively, compared to the considered fixed, computation adaptation, and power adaptation schemes.

As far as total time is concerned, the proposed approach performance is slightly worse than the fixed and computation only adaptation schemes.

CFmMIMO

Authors in [140] proposed a novel scheme for FL-aided CF mMIMO systems that can support any FL framework. An optimization problem to minimize training accuracy, transmit power, and users' processing frequency is formulated as an indicative example, but the authors declare that the proposed framework can have the same outcomes for every FL model. Performance evaluation highlighted the reduced training times by ~55% compared to state-of-the-art approaches. Moreover, the CF mMIMO approach is depicted as the best-performing one compared to CF time-division multiple access massive MIMO and collocated massive MIMO concerning total models' training time. A similar approach, is also, presented by the same authors in [141] to support multiple FL groups. A CF mMIMO to guarantee the stable operation of multiple FL processes is proposed to allow multiple iterations by different FL processes to be executed together. A novel asynchronous algorithm performs the scheduling of the different flows, while a low-complexity RRM allocates the power and computation resources subject to the minimization of each iteration's execution time. Result evaluation indicated that the per iteration execution time can be reduced by ~60% to ~80%. However, a key problem of both of the aforementioned approaches has to do about the *"struggler"* UE effect. A struggler UE is an edge device that slows down the FL training process and communication between edge devices and centralized entity, due to bad link reasons. The approach in [141] selects only a UE subset to take part in the FL process to minimize the probabilities of the *"struggler effect"* to happen. In this case, performance evaluation indicated that FL transmission times can be significantly reduced compared to the previously presented approaches (~30% to ~60%). Finally, the approaches presented both in [142] and [143] propose FL-based CF mMIMO approaches in 6G orientations to reduce the overall execution time and communication overhead in the FL process. Performance evaluation in both approaches confirms the reduced execution time and communication overhead over approaches such as the presented ones in the previous paragraph. However, such effects are more visible when the overall network density levels are low.

RIS

Authors in [15] highlight the advantages of FL approaches, as also, depicted in this chapter, and proposed over-the-air computation as an efficient way to improve communication efficiency and support numerous simultaneous local model uploading. However, in such scenarios, the *"straggler"* effect is present. For this purpose, the authors propose a RIS-aided learning framework for device selection to be used in FL tasks based on model aggregation error and convergence time of the over-the-air FL. Then, a unified communication-learning optimization problem is formulated to optimize device selection and RIS configuration. Performance evaluation indicated that the aforementioned algorithm improves models' accuracy by ~20% compared with the state-of-the-art approaches. These effects are detected even when channel conditions are a lot different across UEs. Similar results are, also, depicted by the same authors in [144]

On the same context, authors in [145] proposed a RIS-aided FL scheme as a countermeasure to the obstacles that are inserted into the FL process by the randomness of channel conditions, focusing on IoT topologies. The goal of this approach is to improve model aggregation/distribution and decrease training times. The total latency minimization problem is formulated, both concerning OFDMA and NOMA multiple access protocols, subject to energy and RIS constraints. Thus, the optimal RRM policies are depicted to efficiently allocate available resources to the UE of the cell under test. Performance evaluation indicated that the RIS-assisted FL scheme can achieve significant latency (~0.5 s) reduction as compared with other benchmark methods. Moreover, the NOMA-based model achieves slightly better training latency than the OFDMA-based one. Similarly, in [146] a RIS-assisted NOMA scheme is proposed to increase the total system's capacity and support UE selection, focusing on total latency minimization. This is achieved by the per training round latency reduction. Then, an auction-based IRS (Winner determination (WD) and payment methods are used) RRM policy is proposed to optimize total latency in the context of multiple-BS model parameters transmission. Performance evaluation indicated that proposed schemes overperform existing ones both concerning training efficiency through device selection and IRS-NOMA RRM optimization. In the field of RIS-aided NOMA 6G networks, *Zhong et. al.* (2022) propose a framework for the sum rate maximization problem using FL and DRL principles. Performance evaluation indicated that a mobile RIS scheme achieves about ~300% sum rate improvement compared to a fixed RIS scheme. Moreover, the NOMA scheme achieves a sum rate gain of ~42% compared to an OFDMA scheme. A similar scheme is proposed in [148] leading, also, in similar results.

Open and Cloud RAN

Finally, concerning distributed computation and MEC employment in 5G/B5G networks, the classical hierarchical structure of a cellular network is proposed to change in order to become more flexible and decentralized. In this framework, O-RAN and CRAN architectures, analyzed in Section II, are about to efficiently satisfy the joint requirements of increased throughput levels with respect to QoS and QoE standards, and also to the concept of low-energy green networks. With respect to the aforementioned considerations, the authors in [149] proposed a deep Q-learning framework in CRAN to maximize EE subject to the constraints analyzed in paragraph 3.1.1. As previously stated, the Q-learning method uses past learning experience to predict future effects and make reward/penalty decisions. However, sometimes action overestimation generates lower probability limits for the maximum Q-value. With the use of a double Q-learning model, the target Q-value generation leaded to bigger energy savings, whereas numerical evaluation indicated that the method reduces by 22% and also, improves EE at the same rate. Considering an O-RAN architecture, the authors in [150] propose an RL based RRM solution and deployed it in the ecosystem. The O-RAN Distributed Unit sends periodically reports to the O-RAN Interface and a dynamic per-flow resource allocation strategy is employed to set the modulation and coding scheme, according to KPI requirements.

3.4 Outcomes

Table 3-1 summarizes the usage of ML in 5G/B5G RRM problems, and groups accordingly the research papers presented in previous paragraphs.

As already stated in chapter 2 and verified by Table 3-1, Supervised Learning techniques are mainly used for prediction purposes. Indeed, various networks' KPIs (throughput, SNIR, pathloss) can be effectively predicted, in order to empower allocation strategies [107]-[109]. DL methods, due to their ability to mine deep data and label associations through multiple complex hidden layers (ANNs, DNNs, CNNs), are mainly used in user, subcarrier, power allocation and CSI prediction tasks [113], [114]. The multiparameter nature of the RRM problem and the complex channel feature associations render DL approaches as the most efficient way to deal with the total RRM problem [110]-[112].

On the other hand, Unsupervised Learning focuses, in general, on clustering: the corresponding models are efficient in user grouping, BS or RN selection and QoS levels formulation, concerning RRM tasks [115]-[118].

RL models -as DL ones do- are more efficient dealing with the NP-Hard problem of the overall resource allocation.

In this framework, RL approaches, such as Q-learning, are proposed by researchers in joint user, subcarrier allocation and energy consumption minimization problems [119]-[126].

Finally, MEC and FL methods, which refer to the most recent evolution in the field, are proposed to face the challenging issue of training time minimization, latency minimization and computational resources optimization. In this framework, MEC and FL methods are combined with either DL algorithms as CNNs, LSTMs, etc. or DRL frameworks -e.g., Deep Q-Learning algorithm- for various RRM-related tasks, such as user allocation, subcarrier allocatio, RN selection [132] – [137]. Moreover, FL methods are combined with other 5G/BG enabling technologies, such as NOMA [45], [138], [139], CFmMIMO [140] – [143] and RIS [15], [144] – [147] to further enhance networks' capabilities and drive research towards 6G implementation.

From the above analysis and Table 3-1, a categorization of the best performing ML algorithms for each RRM-related sub-problem is visible. As presented in Section II, the NP-hardness of the joint subcarrier allocation and power control with respect to QoS, QoE constraints has led recent research efforts to deploy more intelligent solutions, which have the ability to communicate with the cellular environment, and change their predictions and decisions (DL, RL, FL methods), based on the current conditions. However, the existence of big data in transmission systems and wireless networks necessitates the utilization of classical ML approaches, such as supervised ones, specifically in order to tackle problems where the knowledge of a KPI and/or CSI is vital for low latency responses and fast decision making (e.g. for coding and/or modulation scheme selection in each timeslot).

Type of Learning	RRM Problem	Proposed ML approaches	Related Work(s)
Supervised Learning	KPIs prediction (demands, SNIR, throughput, capacity)	SVMs, decision trees, regressions	[107], [108]
Supervised Learning	pathloss prediction	SVMs	[109]
Supervised Learning and Deep Learning	user and subcarrier allocation, power control, CSI prediction	DNNs, CNNs, LSTM, SVMs, Random Forest	[110], [111], [112], [113], [114]
Unsupervised Learning	RN or BS selection	unsupervised *k-NN*, *k-Means* clustering variations	[115]
Unsupervised Learning	user grouping, clustering, handover management	*k-NN*, k-Means, Agg-GNN, f-test	[116], [117], [118], [119]
Reinforcement Learning	subcarrier allocation, power control, frequency selection	MDP, DRL, Water-Filling, WMMSE	[120]. [121], [122],

			[123], [124]
Reinforcement Learning	minimization of difference between requested and active KPIs (throughput, SNIR, CSI)	Deep MARL	[125]
Reinforcement Learning	energy consumption minimization and resource allocation	Q-Learning	[126], [127], [128], [129]
Distributed Learning and MEC	caching CSI information, beamforming	ANNs, DNNs, CNNs	[130], [131]
Federated Learning	power and subcarrier allocation, user scheduling, device selection, relay selection in 6G vehicular networks	FL combined with CNNs and Q-learning, majorize, semidefinite relaxation and Gaussian randomization	[44], [132], [133], [134], [135], [136], [137]
Federated Learning	NOMA	FL deployed DRL	[45], [138], [139]
Federated Learning	CFmMIMO	FL deployed CNNs, ANNs, DRL	[140], [141], [142], [143]
Federated Learning	RIS	FL deployed CNNs, ANNs, DRL	[15], [144], [145], [146], [147], [148]
CRAN/O-RAN	Resource allocation, EE minimization, modulation and cosind scheme selection	CNNs, Q-learning	[149], [150]

Table 0-1: State-of-the-art wors on ML techniques in 5G/B5G RRM

Chapter 4: KPI prediction with Supervised and Deep Learning Techniques

In this chapter the problem of network KPI prediction in 5G/B5G network is discussed. First, the significance of this problem in modern era network systems is highlighted, focusing on the relevance of KPI prediction problem with efficiency RRM strategy formulation. Afterwards, this chapter focuses on throughput prediction, as one of the key metrics regarding the performance of 5G/B5G network to serve the desired QoS of the accepted UEs. For this purpose, several ML/DL algorithms are comparatively examined using public datasets from actual 5G network implementations. The performance evaluation is performed based on both ML KPIs (accuracy, F1-score) and training time needed for each model. With that procedure, the best-performing ML algorithms are identified. Finally, discussion and Open issues are, also, highlighted. In paragraph 4.1 the KPIs of interest in RRM tasks are presented, along with the need for ML-based KPI prediction in 5G/B5G networks. In Paragraph 4.2 the problem of throughput prediction in 5G/B5G networks is examined, where several ML algorithms are evaluated. Results and comparative analysis are, also, performed in this paragraph. Finally, discussion over the results is performed.

4.1 KPIs of interest for RRM tasks in 5G/B5G networks

KPI prediction in 5G/B5G networks is of significant importance for effective network management and optimization. It involves forecasting various performance metrics to gain insights into network performance and make informed decisions. By accurately predicting KPIs such as throughput, latency, coverage, signal strength, and others, operators can optimize network resources, proactively address potential issues, and deliver a better user experience.

First of all, KPI prediction enables proactive resource allocation and optimization. By accurately forecasting KPIs such as signal strength, interference, and capacity, the resource requirements of different areas and user groups can be identified. This information supports the dynamic allocation of the available radio resources, the coverage and capacity optimization and the avoidance of congestion or service degradation [151].

Moreover, KPI prediction assists in interference management. In dense 5G/B5G networks, interference can significantly impact network performance. By predicting KPIs related to interference levels and patterns, interference hotspots can be identified, so that mitigation measures, such as interference cancellation, beamforming, or power control techniques, can be activated to enhance signal quality and minimize interference [152].

Additionally, KPI prediction helps in load balancing and traffic steering. By forecasting KPIs such as user distribution, traffic demand, and mobility patterns, the load across different cells or base stations can be balanced. This enables efficient utilization of radio resources, prevents overloading of specific cells, and ensures a seamless user experience during high-demand periods or in areas with varying traffic patterns [153], [154].

Furthermore, KPI prediction plays a crucial role in optimizing spectrum utilization. By accurately predicting KPIs related to spectrum availability, utilization, and efficiency, spectrum resources can be efficiently managed and allocated. This includes techniques like spectrum sharing, cognitive radio, and dynamic spectrum access, which enable efficient utilization of the available spectrum and support diverse services and applications [155].

KPI prediction, also, supports network planning and optimization. By analyzing historical KPI data and using predictive models, future network demands can be determined, and, thus, capacity expansions can be planned and network deployment strategies can be optimized. This includes determining the optimal placement of base stations, adjusting antenna configurations, and optimizing parameters to meet performance targets and ensure efficient resource usage [156].

When considering throughout as the KPI to predict, there are some more RRM-related field that the a priori prediction of the anticipated system or user throughout can be really significant. In fact:

- QoE Optimization: Predicting throughput helps in optimizing the user experience by ensuring sufficient bandwidth for demanding applications and services. By forecasting throughput, the potential congestion or performance bottlenecks can be identified and proactive measures can be taken to maintain a desired QoE level, such as adjusting resource allocation, prioritizing traffic, or applying traffic shaping techniques [157].
- Service Level Agreement (SLA) Compliance: Accurate throughput prediction is essential for meeting SLA requirements and contractual obligations. By predicting throughput and monitoring its performance against defined thresholds, operators can ensure adherence to SLAs and deliver the promised performance to customers. This enables proactive measures to maintain customer satisfaction, avoid penalties, and manage service level expectations [158].

4.2 Throughput prediction in 5G/B5G Networks

In this paragraph, the performance of various ML algorithms for KPI prediction is presented. The investigated ML algorithms have been selected based on two criteria. The first criterion is their ability to satisfactorily solve the KPI prediction problem. This means that we have selected algorithms with performance scores over 75% in accuracy. The second criterion is the usage of these algorithms in RRM-related KPI prediction tasks in 5G/B5G networks, according to the presented literature in the previous chapters (basically in section 3.3 of chapter, i.e., [25], [107], [108], [116]-[118]). More specifically, using the Lumos-5G dataset [158], the problem of throughput prediction is investigated (Lumos5G features are, also, summarized in Table 4.1).

4.2.1 Dataset and problem formulation

Lumos 5G dataset [158] contains 68,118 observations of 19 features, concerning UEs' location and mobility parameters, such as longitude, latitude, UE speed and direction, UE-BS distance and corresponding angles, as well as network related ones, such as network status (connected or not), CSI parameters (Received Signal Strength Indicator - RSSI, Reference Signal Received Power - RSRP, Reference Signal Received Quality - RSRQ, SNIR), and signal strength, derived by real-world experiments and statistical analysis. The measured downlink throughput acts as the response variable. All these features are depicted, also, in Table 4.1.

Feature	Description
timestamp	day, time logs
longitude, latitude	Geographical coordinates for each UE
detected activity	walking, still, driving
moving speed	UE’s moving speed using Android API
compass direction	horizontal direction of travel of each UE
radio type	5G or 4G
cell IID	number of the BS that each UE is assigned to
signal strength KPIs	RSSI, RSRP, RSRQ, SNIR
UE to BS distance	distance between each UE to the server BS
positional angle	angle between each UE and the corresponding BS
mobility angle	distance between each UE’s trajectory route and the corresponding BS
throughput	downlink throughput using iPerf 3.7

Table 0-1: Lumos 5G dataset's features

Throughput prediction is formulated, either as a classification or as a regression problem. On the one hand, classification refers to the prediction of the received throughput level by each active UE, given the dataset features. The effective solution of this problem can be valuable in a variety of RRM-related tasks, such as modulation levels definition.

Considering throughput prediction as a classification problem, two different approaches are considered in our analysis. The first one concerns three preselected throughput levels (3 classes):

- *Level 0 - low throughput:* from 0 to 300 Mbps,

- *Level 1 - medium throughput:* from 300 to 500 Mbps, and
- *Level 2 - high throughput:* above 500 Mbps.

However, due to the small amount of data in the second class of the previous approach, we consider also an alternate approach, where two preselected throughput levels exist (2 classes):

- *Level 0 - low throughput:* from 0 to 300 Mbps,
- *Level 1 - medium throughput:* above 300 Mbps.

The above-presented level limit values -in both 2-class and 3-class approaches- have been generated after performing extensive statistical analysis to the used dataset, concerning the goal of including satisfactory samples in each investigated class.

On the other hand, regression refers to the prediction of the actual expected value of the metric (throughput in our case). The information gathered by the regression task can be valuable in RRM decision tasks, such as subcarrier and/or power allocation, via the prediction of the values for next timeslots.

4.2.2 Implemented ML algorithms

4.2.2.1 Throughput prediction as a classification Problem

Considering throughput prediction problems as a classification one, the following four distinct ML-based algorithms are examined:

- *FFNN:* A Feedforward NN with 100 hidden layers and rectified sigmoid activation function (ReLU) and optimized hyperparameters,
- *k-NN:* A *k*-NN-based classifier using 2 neighbors and Chebyshev distance criterion,
- *SVMs:* Two SVM models, one using polynomial and another using Gaussian kernel and
- *DNN:* A Deep NN with a feature input layer -using the 19 features of the dataset- and z-score normalization, a fully connected layer with 19 - 50 weight matrix and a 50-element vector output, a 50-channel batch normalization layer, a ReLU layer with a 50-element vector output, a second fully connected layer with 3 or 2 (3-class and 2-class problem respectively) neurons and 50 × 3 (3-class problem) or 50 × 2 (2-class problem) weight matrix and a 3-element/2-element vector output and, finally, a soft-maximization layer with a 3-element/2-element vector output. The overall DNN's structure for the 3-class problem is shown in Fig. 4-1. DNN's structure for the 2-class problem is similar and differs only in the size of the two last layers (fully connected layer 2, soft-max layer).

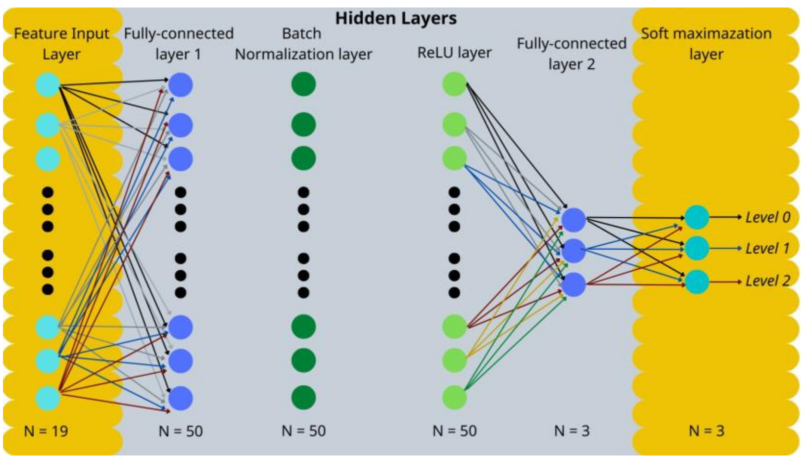


Figure 0-1: DNN's architecture

4.2.2.2 Throughput prediction as a regression Problem

Considering throughput prediction as a regression problem, the following algorithms are examined:

- *Linear regression:* A multi-linear regression model, using all 19 dataset features except throughput, which is the response variable,
- *Binary Decision tree:* A Gaussian binary decision tree designed for regression purposes, using auto-optimized hyperparameters,
- *SVMs:* Two SVM models, one using polynomial and another using Gaussian kernel and,
- *NN:* A Feed Forward neural network with 100 hidden layers, a feature input layer with the 22 features of the dataset and z-score normalization, a 50_50 fully connected layer, a 50-channel batch-normalization layer, a ReLU layer, a soft-maximization layer and a regression layer.
- *LSTM:* A LSTM neural network with a sequence input layer for the 22 features of the dataset, an LSTM layer with 125 hidden units, a fully connected layer and a regression layer.

4.2.3 Results and Comparative Analysis

In both of the abovementioned approaches (studying the KPI prediction problem in 5G/B5G networks either a classification or regression one), an 80%-20% training-test set split has been used, as well as a 10-fold cross validation procedure.

4.2.3.1 Throughput prediction as a classification Problem

The performance of the abovementioned classifiers is evaluated, using the accuracy and F1-score metrics. Accuracy is the percentage of the total number of the correct predictions divided by the total number of observations. In other words, accuracy is given by the sum of True Positive (TP) and True Negative (TN) predictions, divided by the number of the total predictions (TP + TN + False Positive (FP) + False Negative (FN)), as depicted in the following formula (see also the confusion matrix in Fig. 4.2):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

Then, F1-score is given by the formula (12), by utilizing formulas (10), (11), which describe Precision and Recall metrics:

$$Precision = \frac{TP}{TP+FP} \quad (10)$$
$$Recall = \frac{TP}{TP+FN} \quad (11)$$
$$F1_{score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a: TP	b: FN
	Class=No	c: FP	d: TN

a: TP (true positive)
b: FN (false negative)
c: FP (false positive)
d: TN (true negative)

Figure 0-2: Confusion Matrix

Table 4-2 summarizes the performance of the above models in the classification task (with two or three classes), based on classification accuracy and F1-score. The *k*-NN-based approach overperforms all the other approaches, witnessing the best overall accuracy (0.87 and 0.90 with three and two classes, respectively). In general, supervised learning algorithms (such as *k*-NN) are the most appropriate ones in networks' KPIs prediction, as drawn from the existing literature, analyzed in subsection E of section III. However, concerning F1-score, DNN has the best performance (0.81) in the 3-class problem, while *k*-NN (0.90) in the 2-class model.

ML Algorithm	3-classes		2-classes		Training time (s)
	Accuracy	F1-score	Accuracy	F1-score	
FFNN	0.81	0.67	0.88	0.88	960.41
k-NN	**0.87**	0.77	**0.90**	**0.90**	**111.79**
SVMs	0.76	0.53	0.82	0.82	150.03
DNN	0.81	**0.81**	0.85	0.84	129.43

Table 0-2: ML Classification algorithms comparison

As, also, stated in paragraphs 3.4, DL algorithms, due to their multiple hidden layer architecture, witness unseen aspects of the dataset, and, thus, their performance is satisfactory in the classification task. In this case, the preselected classes are imbalanced. Therefore, F1 metric is more reliable, because it concerns both TP, TN and FP, FN, while accuracy takes into account only TP, TN. It is also visible from Table 4-2, that, using only two classes, both accuracy and F1-metrics are improved. Moreover, with respect to the training time of each ML model we observe that *k*-NN overperforms the other approaches, while the DNN approach reaches almost the same performance levels. Thus, these two ML methods are the most appropriate for the investigated problem in both performance and training time perspective. On the other hand, *FFNN* approach has significant delay in training time, even though the performance accuracy almost coincides to the best-performing algorithm's one.

A second level of performance evaluation is to compare the best-performing algorithms presented above (in terms of Accuracy and F1-score) with similar works presented in the literature. In this direction, Figs. 4-3, 4-4 depict the comparison of selected state-of-the-art throughput classification approaches [159]-[161] while the previously presented evaluation analysis is included as well.

For each of the [159]-[161] works, we pick the best performing ML algorithm, and so we do for our evaluation approach, as far as the 3-class throughput prediction problem is concerned (i.e., *k*-NN algorithm, see Table 4-2). As it is apparent, our evaluation approach is consistent with similar approaches in other recent works [159]-[161].

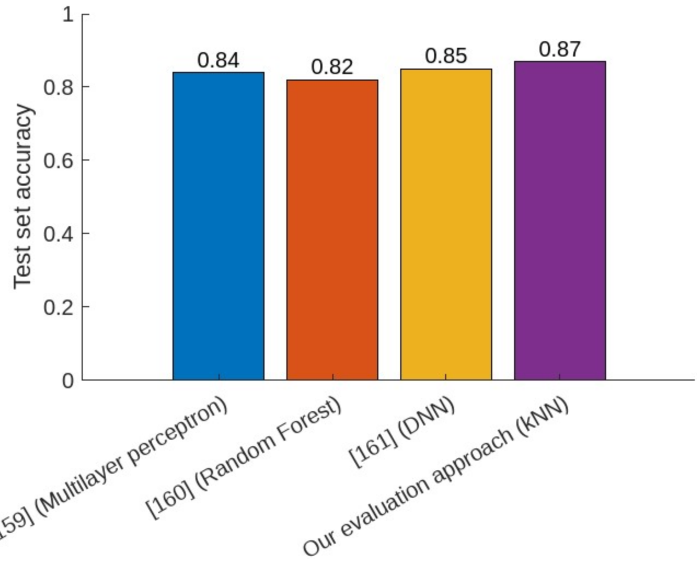


Figure 0-3: Classification models comparison: accuracy

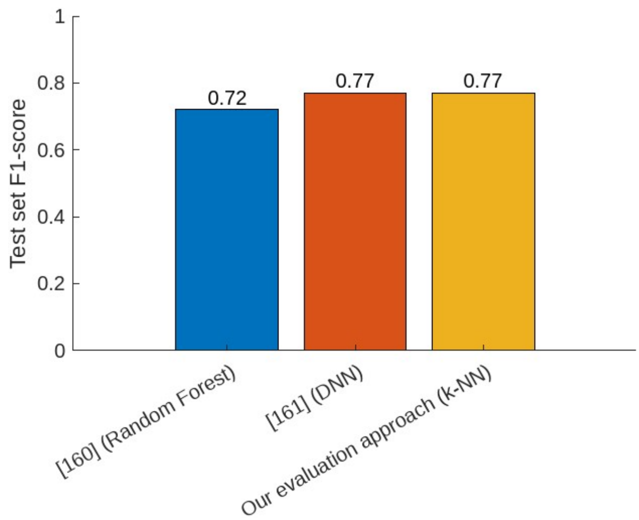


Figure 0-4: Classification models comparison: F1-score

4.2.3.2 Throughput prediction as a regression Problem

The performance of the abovementioned ML models is evaluated using the mean absolute error (MAE) and RMSE metrics. MAE is defined as the difference between the actual and the predicted values of the response variable (throughput), while RMSE is defined as the square root of the squared difference between the actual and predicted values, as depicted, also, in the following formulas:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \cdot 100\% \ (13)$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \ (14)$$

Where, y_i is the actual value of the i^{th} observation of the test dataset and $\hat{y}_i$ is the prediction for the i^{th} observation of the test dataset from a specific ML algorithm.

Table 4-3 and Figs. 4-5, 4-6 summarize the performance of the above models in the regression task, based on MAE and RMSE. The two best performing ML-based approaches are Binary Tree regressor and LSTM regressor, witnessing the best overall MAE and RMSE performance (162,257 and 150, 250 respectively). As in the previous case (classification problem), supervised and Deep learning algorithms are the most appropriate ones in networks' KPIs prediction as a regression problem. In fact, decision tree algorithms and linear regressors are designed for regression purposes. However, NN model's performance is also highlighted, as it is the second best in both metrics (237 and 328, respectively).

Fig. 4-7 depicts the comparison of the state-of-the-art throughput prediction approach in [113] with our previously presented evaluation analysis for the regression problem. We pick the best performing regression ML algorithm of [114], and so we do for our evaluation approach.

(i.e., LSTM regressor, see Table 5). The comparison is conducted using RMSE as metric. As it is apparent, our evaluation approach is consistent with the approaches in other recent works [114].

ML Algorithm	MAE	RMSE	Training time (s)
Linear Regression	278	353	1.05
Binary Decision Tree	162	257	50.61
SVMs	278	354	28.54
NN	237	328	**6.89**
LSTM	**150**	**250**	276.89

Table 0-3: ML Regression algorithms comparison

To conclude, we observe that, in general, both our approaches and other recent works on the KPI prediction problem for 5B/B5G networks propose Supervised or DL models as the most appropriate tools for this type of problem either as a classification or a regression one. On the one hand, supervised learning models (*k*-NN, SVMs, Random Forest) seem to have the best performance concerning training time. But on the other hand, DL (DNNs, LSTM) models overperform when it comes to performance metrics, such as accuracy and F1-score for classification purposes or RMSE, MAE for regression ones.

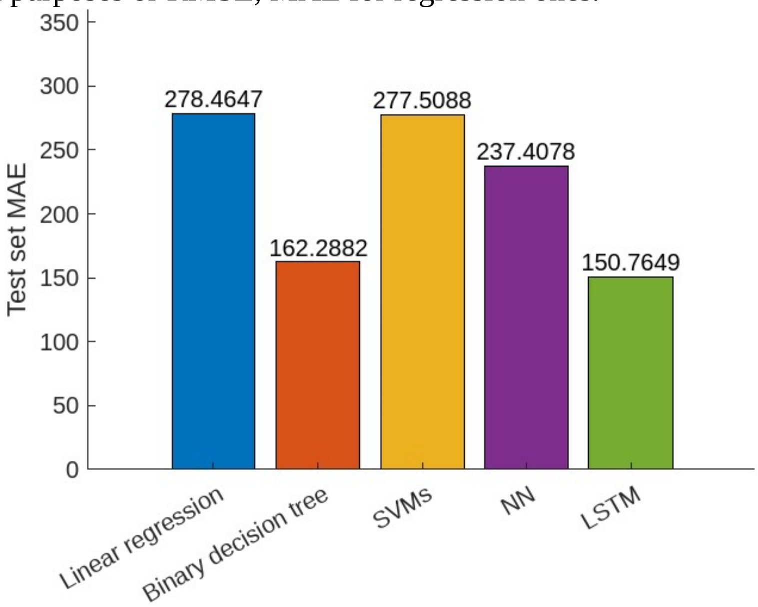


Figure 0-5: Regression models: MAE

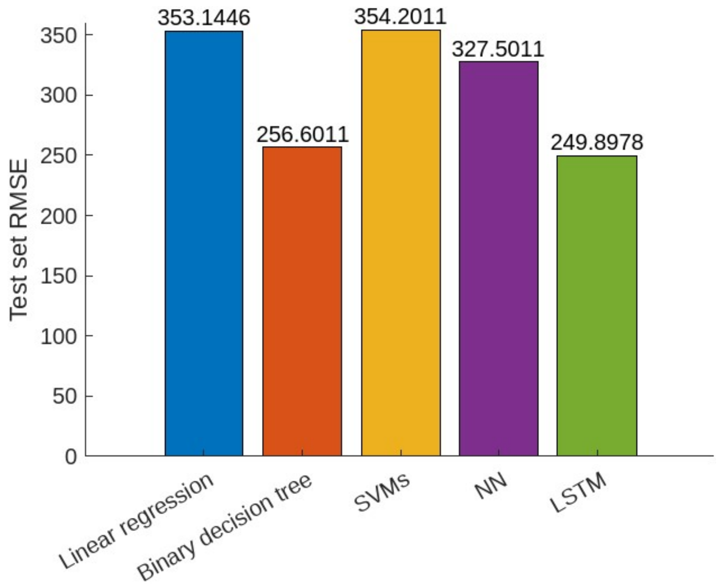


Figure 0-6: Regression models: RMSE

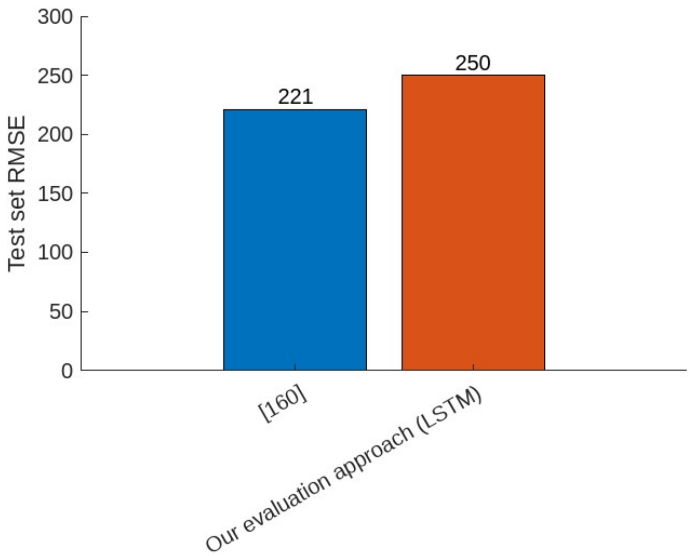


Figure 0-7: Regression models comparison: RMSE

4.2.4 Discussion and Open Issues

As already presented in Chapter 3, the allocation of the available network resources is a multi-objective problem, due to the diverse nature of users' requirements, hardware evolution and demand for continuous connectivity. Despite the research progress presented in section 3, some open questions and practical challenges persist, requiring even more effort in the field of ML-based RRM, to reach its full potential. These issues have been, also, identified throughout the performance evaluation of the different ML algorithms regarding the throughput prediction problem in 5G/B5G networks. The critical issues that should be taken into consideration are highlighted below and summarized in Table 4-4.

First of all, 5G and B5G networks utilize ML-based algorithms to phase the growing number of usage scenarios in access management. Therefore, ML performance metrics (such as RMSE for regression problems, accuracy for classification ones, etc.) should be examined along with the network metrics (i.e., total network throughput, QoE, etc.) [107], [115]. Some approaches (e.g. [25], [112]) focus only on the ML metrics performance increase, without also evaluating the networks' metrics.

Throughout this thesis, the critical role that AI/ML plays in wireless networks and in IoT and heterogenous topologies has been highlighted. However, researchers should not overlook some practical limitations that exist in the implementation process of ML-based RRM strategies, i.e., when developing the corresponding ML model. More specifically:

- *5G datasets unavailability and/or poor quality:* A key procedure for building ML models is the validation and training stage. 5G full deployment throughout the world was set for 2020, before the COVID-19 pandemic. Hence, 5G data from implemented networks have only recently started to be produced. The AI/ML models, that have been produced until now, are using synthetic or incomplete data from past networks' generations [42]. Another aspect that also affects data quality is the fact that, in general, wireless network data are characterized by noise and inaccuracy. In fact, even well-established wireless network datasets -such as DeepMIMO [162]- witness quality issues in a variety of RRM-related problems. We should also keep in mind that, due to the highly interference environment, huge datasets, including numerous features and observations, are, anyway, required. All the data-related limitations presented in this paragraph, prevent ML models from reaching high levels of accuracy; lack of input leads to suboptimal or non-optimal solutions. This consideration reflects every ML-based model, regardless the type of learning. Both supervised, unsupervised, reinforcement or deep learning approaches have insufficient results when the quality of the input data is moderate.
- *Learning difficulties due to channel complexity in multiuser environments:* 5G wireless networks are characterized by multipath propagation in a highly interferenced environment. This, as stated previously, consists one of the reasons for the need for an enormous variety of features and channel observations in ML datasets construction for RRM (preferably Big Data). Hence, feature extraction for channel information becomes a demanding task. Linear models and generic algorithms (such as simple-tree models, regressions, etc.) are unable to provide optimal solutions, concerning effective resource allocation. The approaches discussed in previous sections configure ML-algorithms by alternating hyperparameters and evaluate accuracy in the RRM sub-problems. In this context, performance and models' selection policies are vital in ML-based approaches. Researchers should have deep knowledge of the ML models, pre-trained or not, so that they become able to correctly evaluate them [163]. Concerning the complexity of the channel and the growing users' demand in 5G/B5G networks, DL methods are proposed as the more efficient ones.
- *Computational complexity:* In terms of accuracy, the AI/ML models discussed in previous sections have improved performance, when used to solve complex problems based on networks' KPIs. Concerning the URLLC requirements and the demand for mass access to the medium in 5G/B5G networks, RRM decision making should be done with respect to computational complexity. However, the highly interferenced environment and random mobility patterns of UEs act in the opposite direction. Thus, ML techniques should succeed in proposing a trade-off between the solution's accuracy and computation requirements [109], [117],[124]. Even though DL solutions are proposed as the most efficient ones, they increase computational complexity, by employing multiple hidden layers to yield accurate results. In this respect, distributed approaches using MEC architectures and FL-based algorithms should be considered. Taking also into account the requirement for energy efficient networks, researchers should maintain the computational cost to tolerable levels [110], [115].

Finally, Power consumption rapidly increases in 5G, and will further increase in B5G networks, compared to previous generations, due to the users' growing demands for continuous access to enhanced services and applications. ML schemes, if effectively implemented, contribute to power savings, as, hopefully, they lead eventually to fast and more accurate RRM decision-making. For further energy consumption mitigation, we should incorporate energy-efficient technologies during the models' training phase, where additional computational resources are needed. In this direction, Green AI techniques and distributed processing methods (such as MEC) should be further investigated, so that less energy harvesting solutions become feasible [164].

Open Issues	**Potential Solutions – Suggestions for future Work**
networks' KPIs and ML KPIs joint evaluation [24], [113]	ML methods' evaluation in terms of network performance [25], [123]
5G datasets unavailability and poor quality [42], [162]	research work in dataset generators, real-world data availability [158], [159]
channel complexity [128]	DL approaches [159]
computational time and cost [108], [117], [122]	distributed DL, use of MEC and FL [109], [114]
energy consumption [165]	MEC, Green AI technologies [165]

Table 0-4: Open issues and potential solutions concerning ML employment in RRM

Chapter 5: Relay Node Placement and Selection in 5G/B5G Networks

In this chapter the problem of ML/DL-enabled RN placement and Selection in 5G/B5G network is discussed. As presented in Chapter 1, RN utilization is one key enabling PHY technology that can extend the coverage area of each cell in 5G/B5G networks, while capacity and maximization of the accepted UEs to be served, can be, also, achieved. First, a state-of-the-art review is performed regarding the ML-schemed used for RN placement and selection in 5G/B5G systems. Afterwards, the RN placement problem is mathematically formulated. In order to propose several ML-based solutions on that problem, the lab's 5G/B5G system and link level simulators is utilized in order for synthetic datasets to be produced. Thus, the dataset generation flow is, also, discussed in this chapter. Afterwards, two DL-based schemes trained either CL-based or FL-based are presented, while the corresponding performance evaluation outcomes are analyzed. The second part of this Chapter discusses the problem of RN selection in 5G/B5G networks. In this context, the problem is mathematically formulated subject to the relevant PHY constraints. Afterwards, a DRL (Deep Q-Learning) scheme is proposed as a solutions to the aforementioned problem. This scheme considers the joint maximization of each UE's EE and SE, and the maximization of the overall system's EE and SE. Discussion over the aforementioned approaches and the results after simulations are, also, considers. Considering all the above, in paragraph 5.1 an introduction to ML/DL-based RN placement and selection is performed. In paragraph 5.2 a literature review over the exiting ML/DL-based schemes for RN placement and selection in 5G/B5G networks is performed. In Paragraph 5.3 the problem of RN placement is formulated and two DL models are proposed and evaluated to optimally solve this problem. Moreover, both approaches are trained either in a CL or an FL way. By that comparison, the training time gains of the FL approach are compared to the ML KPIs (e.g., accuracy, F1-score) maximization gains of the CL one. Paragraph 5.4 considers the problem of RN selection (over several candidate RNs) for each accepted UE in the topology. In this framework, the problem is mathematically formulated, while a Deep Q-Learning approach which maximizes EE and SE is proposed. This approach is evaluated via numerous simulation rounds.

5.1 Introduction

In recent years, 5G/B5G wireless communications systems have been established to support the exponential growth rate of mobile data traffic [1]. Moreover, the rapid evolution of wireless services, drove 5G/B5G standardization process to deal with different telecommunication service categories, such as URLLC, eMBB and mMTC in mass access environments [165], [166]. In this context, various novel physical layer technologies have been introduced over the last years to cope with the increasing challenges in the wireless communications domain, such as m-MIMO configurations, mmWave transmission, as well as NOMA [167]. However, the aforementioned advanced PHY technologies, when applied in a cellular environment characterized by high interference levels and complex channel approximations, along with increased connection density and near-random user mobility patterns, maximize the computational cost to support strict users' requirements and demands. ML algorithms are proposed as an efficient way to tackle these considerations, due to their ability to utilize data generated by the network itself in improving network performance and efficiency [168]. ML algorithms are trained using either data generated by the wireless network under test or by similar ones. In this way, complex channel calculations are encapsulated in ML models' layers, which leads to the decrease of computational cost and complexity after successful training rounds. Moreover, some ML algorithms (e.g., RL ones), can directly interact in real-time and support low-latency requirements of modern era networks.

The 5G/B5G network architecture is based on the heterogenous networks (HetNets) model in order to meet the increased network capacity and ultra-density requirements. HetNets involve the composition of a number of smaller, simpler, and lower-power BSs, with different characteristics (transmission capacities, coverage areas, carrier frequencies, etc.) to improve cell-edge coverage and enhance the network KPIs [169].

However, there are cases even in HetNet topologies, where the coverage area of each cell should be extended for more users to be served by the network. Such scenarios are of significant interest in Unmanned Vehicles (UxVs) scenarios or military/defense networks. In this context, RNs have been proposed as a "retransmission technology", that can relax transmission burden from centralized BSs. Thus, by using RN-assisted RRM mechanisms, total system's performance can be upgraded by further improving data rates, mitigating interference levels and extending network coverage [CONF-1]. An open research field concerning the use of RNs in multicellular 5G/B5G networks is the optimal relay placement within each cell's area, to improve various network KPIs, such as total served users, achieved throughput and SNIR, total transmitting power and blocking probability. Moreover, the selection of the optimal RN, from the candidate ones, to serve each active UE in the topology is, also, of the same interest. Compared to an established one-hop downlink communication link between a BS (transmitter) and a UE (receiver), an n-hop relaying-assisted BS-UE link's complexity is increased due to the following reasons:

a) The use of RNs was introduced in 3GPP release 16 [170], while the beginning of standardization process can be found in release 17 (latest stable edition of 3GPP documents) [171]. This means that there are no detailed channel, pathloss and mobility models for RNs.

b) The effectiveness of the RN-UE connection is based, also, on the quality and stability of the BS-RN link.

c) Shared resource management should be performed, as RNs are a layer 3 (L3) entity, which needs BSs' assistance in performing advanced RRM tasks.

Recently, ML is proposed as an efficient approach to deal with the abovementioned problems of optimal RN placement and optimal RN selection between candidate RNs [172].

The key characteristic of ML-based approaches is that -using data generated by existing systems-, they can accurately estimate the examined system's behaviour, with the minimum computational cost. In this way, complexity is reduced, and accurate predictions can be performed leading to real-time responses. This chapter focuses on solving the joint problem of RN placement and selection by utilizing different ML-based techniques, focusing on DL and RL. These chapter's contributions can be summarized as follows:

- The problem of RN placement to maximize the number of active users in each cell of the cellular topology is mathematically formulated. Thus, given only the number of the RNs per cell to be deployed and a set of potential geographical positions (x-y coordinates of potential RNs), the *k* best-performing RNs are selected to serve the active UEs in each cell. The aforementioned selection is performed subject to three main constraints. The first one is the minimization of pathloss for each accepted UE, the second refers to the minimization of the total transmitted power by each deployed RN, while the latter is the maximization of the total accepted users in the topology. Moreover, the proposed algorithm is tested in two different simulation scenarios. The first one considers the presence of ideal CSI, while the latter considers no CSI at all.
- To tackle the aforementioned problem, two efficient offline RN placement ML/DL algorithms are proposed. These algorithms focus on fast response times by taking into consideration the constraints of the previous bullet. The fist DL algorithm considers a Deep ANN orientation, while the latter considers a LSTM one.
- After the optimal placement of the RNs in each cell's coverage area, the problem of optimal RN selection for each accepted user in the topology is formulated. In other words, for UEs not served directly by the BSs, either for pathloss or power consumption reasons, the optimal RN (from the *k* eligible) should be selected to serve them.
- To solve the aforementioned problem, an energy efficient RL-based algorithm to select the optimal beam (RN) to serve each accepted user in the topology is proposed. A DRL, (Deep Q-Learning) algorithm is utilized for this scope. In this context, EE and SE are the KPIs that determine algorithm's transitions.
- Finally, all presented approaches are evaluated by extensive system level simulations in different usage scenarios. Performance evaluation indicates that the joint DL based RN placement and selection scheme can overperform state-of-the-art approaches in improving various network KPIs, such as EE and SE.

5.2 Existing Literature Review

Algorithms for RN placement and selection is an active area of research in wireless communications, especially in 5G/B5G cellular communication networks. In fact, the implementation of relaying-assisted communications is proposed in different usage scenarios in modern era wireless systems, such as MANET/WANET networks, supply chain management and manufacturing. Moreover, the joint utilization of RN-assisted communication and modern multiple access schemes, e.g., NOMA, are also of high research interest nowadays. In these cases, the NP-Hard optimization problem [172] of RN placement and/or selection is solved through either distance-based techniques with the use of graph theory or game theory [173], [174], or via extensive search algorithms (e.g., using ergodic capacity analysis) [175]. Furthermore, moving RNs are, also, under research, due to the growing interest in UAV communications [176].

In this framework, ML-based solutions are investigated as an efficient way to deal with the NP-Hardness of the aforementioned problem. The current research activities on the field of ML-assisted RN placement and selection are presented in this paragraph. The concept of ML-assisted RN placement is introduced in [177]. Authors presented an optimal RN positioning method, aiming to improve system's performance in uncertain and dynamic-changing multicellular topologies. Consequently, channel quality prediction in both BS-RN and RN-UE link is of primary concern in defining RN positioning. Authors proposed a learning-based and a distance-based method for channel prediction based on mobility patterns of RN under test. The achieved connectivity levels are used as the basic KPI during performance evaluation. A heuristic optimization algorithm is used for optimal RN positioning, outperforming a recently developed relay positioning algorithm.

In [172], an approach for deploying the minimum accepted number of RNs -as a subset of given potential locationsis considered with respect to QoS requirements in multihop wireless systems. A hop count boundary is inserted to ensure a certain blocking probability in the BS-RN link. To deal with the NP-Hardness of the RN placement problem, a polynomial time approximation algorithm using shortest path trees and heuristically pruning the relay nodes used until the hop count bound is violated, is proposed. Performance evaluation indicated that this approach efficiently solves the abovementioned problem in various randomly generated network scenarios. More specifically, optimal solutions are given in over 90% of the tested scenarios. Afterwards, authors used random graph techniques to derive an upper bound on the average case approximation ratio for the used algorithms based on the number of source nodes, and the hop count bound. This average case analysis was the first one in RN placement literature.

On the other hand, authors in [178] face RN placement problem as a clustering one. The scenarios of interest consider Wireless Sensor Networks (WSNs), where RNs are used as mediators between users and applications' servers by assisting messages transmission. A k-means clustering ML approach is activated for link restoration whenever it is necessary based on transmitting power, number of packets lost in a RN-BS link and BS-UE distance. Thus, for each BS, the corresponding RN is deployed at the most frequently used route in the network. Numerical evaluation indicated that the proposed method outperforms existing distance-based methods on the basis of various KPIs such as residual energy, endto-end delay and the number of hops required in the network from source to destination. Moreover, k-means clustering algorithm implementation can reduce the total number of used RNs.

Considering industrial WSNs, authors in [179] studied the placement of RNs in a realistic three-dimensional (3-D) factory space based on the satisfaction of various physical, performance and energy-related KPIs. The study was performed using IEEE 802.15.4e low latency deterministic network mode in order to achieve low latency and highly reliable communications in harsh factory environments, which are suffering from noise, interference and multipath fading. Hence, frequent packet losses are reported. The authors proposed the joint incorporation of RN nodes and forward error correction (FEC) techniques leading to enhanced communication reliability. More specifically, on the one hand an efficient and pragmatic relay-placement strategy based on rainbow product ranking algorithm for a 3-D factory space, and on the other hand an adaptive RL transmission scheme (using Q-learning techniques), which incorporates cooperative diversity and Reed Solomon block codes, are proposed. A real-world case study is performed in order to evaluate the correctness and effectiveness of the presented solution. The proposed RN placement strategy has improved performance in terms of cost reduction and total number of deployed RNs compared to other state-of-the-art approaches. Moreover, the used Q-learning method efficiently utilized the resources in terms of relays and BSs, making the transmission scheme more generic in terms of, not only adopting to versatile factory environments but also accommodating the dynamic behaviour per link in the factory space.

A more complex scheme considering not only RN localization but also power management in 5G networks is presented in [180]. A mathematical analysis for defining expressions and minimum threshold for end-to-end average symbol error rate (SER) and outage probability (OP) is performed for in amplify-and-forward (A&F) RNs, introducing those KPIs as the main ones for the problem definition. As a result, the high correlation between BS-RN and RN-UE links, is described. Afterwards, the joint power allocation (PA) and RN placement problem is considered. Results indicated that RN placement optimization is more efficient than PA. Thus, an ML implementation of the proposed convex optimization problem is investigated. The joint problem is translated to a regression ML problem and authors propose a feed-forward neural network (FNN) approach (2 and 3 hidden layers are considered). ML-models' performance is controlled using the mean absolute percentage error (MAPE) metric which reached over 90% score. The simulation results demonstrated a compromise between MAPE and computation times for the FNN-based joint PA-RL optimization.

Authors in [181] proposed a combined RN selection and resource allocation (RA) algorithm. A key drawback in existing approaches is the need for a large number of relays to forward signals transmitted on multiple subcarriers. However, signal generation in multi-hop scenarios increases the complexity of combined RN selection compared to that of per-subcarrier relay selection, when the number of relays increases. In dense 5G networks, the impact of that problem is even bigger. To deal with this drawback, authors proposed a supervised ML method. The training phase is implemented off-line, leading to a considerable reduction to the RN selection complexity and the processing latency. An ANN scheme is used for the best couple of relays to be selected. In each epoch the least accuracy criterion is checked to continue simulations. Accuracy and Mean Squared Error (MSE) are the two considered KPIs for ANN's performance. Numerical evaluation indicated that the proposed supervised ML approach can provide near-optimal performance with lower computing latency, which nearly reaches the optimal relay selection in a per-subcarrier manner. Over the last years, RL-assisted RN selection and RA have attracted scientific research interest as well.

In this context, Geng et al. in [182] studied the joint outage probability minimization, RN selection optimization and transmission power reduction problem in RN-assisted 5G networks, where the existence of accurate CSI is extremely difficult. Thus, the authors proposed an RL prioritized experience replay aided framework, acting in optimal solution finding to the above-mentioned problem without any prior knowledge of CSI. The proposed approach is compared to other RL-based solutions, and performance evaluation indicated that communication success rate can be improved by about 5%.

On the same context, the authors in [183] proposed an RN selection algorithm to succeed in providing guaranteed reliability, low latency, and power consumption levels in large scale multi-hop 5G topologies. The proposed scheme uses Q-Learning RN selection based on SNIR levels. Q-learning is an RL approach, which consists of an agent, the environment, agent's states, actions, as well as rewards or penalties. In learning stage, the agent learns the optimal allocation policy to maximize the reward [184]. From network's perspective, the BS knows the optimal RN to select and transmit the signal. The used RNs are decode-and-forward (D&F) ones, and the system uses orthogonal frequency division multiple access (OFDMA) techniques. Finally, the proposed scheme tries to utilize optimal allocation policy based on the learning outcomes of the previous stage, based on the SNIR. Performance evaluation indicated that the proposed approach achieves the same bit error rate (BER) levels as conventional RN selection schemes in the literature. The basic advantage of the proposed approach is the selection of fewer RNs when the target BER is satisfied. Consequently, system's latency is improved.

The aforementioned research efforts describe some aspects of the utilization of Artificial Intelligence (AI)/ML methods for the optimization of either the problem of RN placement or RN selection -over a set of available RNs- in wireless systems. However, most of these works evaluate the proposed algorithms in single-cell orientations, or by limiting the number of active UEs in the topology. Our motivation is to extend these works and present a global ML-based framework to both train an offline ML model to place the RNs based on the performance of simulated UEs in the topology, but also, propose an RL method to interact with the cellular environment and select the best-performing RN for each accepted UE in the topology. The motivation of this chapter is to extend these works and present a global ML-based framework to both train an offline ML model to place the RNs based on the performance of simulated UEs in the topology, but also, propose an RL method to interact with the cellular environment and select the best-performing RN for each accepted UE in the topology. The outcomes of the ML/DL/DRL frameworks that are proposed in this Chapters have been, also, published in [J-2].

5.3 ML-assisted Relay Node Placement

5.3.1 Problem Formulation

The downlink of a cooperative wireless OFDMA 5G/B5G multicellular HetNet is considered, as illustrated in Fig. 5-1. The studied system has two different levels of base entities. The first one, Macro-BSs, forms the primary system where UEs can directly access and request service. The latter one, RNs, form the secondary system, aiming to assist the primary system in improving capacity and coverage area, by serving UEs that have been initially rejected by the primary system.

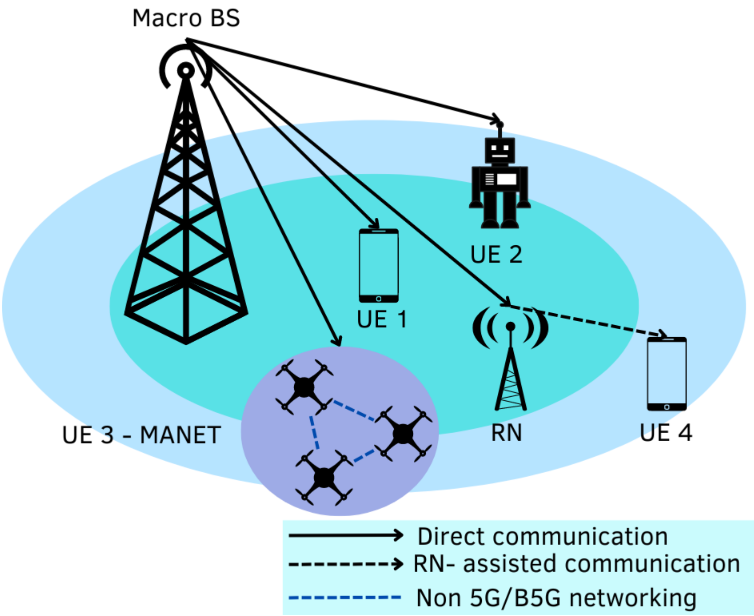


Figure 0-1: Two-hop 5G/B5G HetNet with A&F RNs

Thus, the cooperative system consists of M BSs, R RNs and N uniformly distributed UEs. The set of BSs is denoted as $S_b = \{b_1, b_2, \ldots, b_M\}$, the set of RNs is denoted as $S_r = \{r_1, r_2, \ldots, r_R\}$, while the set of UEs is denoted as $S_u = \{u_1, u_2, \ldots, u_N\}$, respectively. The potencial link between a BS and a UE is denoted as $L_{b,u}$ where $b \in S_b$ and $u \in S_u$, the potential link between a BS and a RN is denoted as $L_{b,r}$ where $b \in S_b$ and $r \in S_r$, while the potential link between a RN and a UE is denoted as $L_{r,u}$ where $r \in S_r$ and $u \in S_u$. Note that the Cartesian coordinate system is used to locate all enrolled entities both considering 2D or 3D space.

As previously stated, RNs are deployed to assist the primary communication's system to support UEs that are initially rejected due to high pathloss or other power allocation reasons. The goal of this sub-problem is to select the N_{CRN} positions (set of x-y-z coordinates) for the best-performing RNs to be deployed in each cell's coverage area. Best performing RNs are selected to optimally meet user requirements and maximize each cell's performance. Thus, a predefined number of potential RNs are placed in different positions inside each cell's coverage area, declared as RN_{can}. Fig. 5-2 provides an illustration of such a topology for a single 5G/B5G cell where $RN_{can} = 10$ candidate RNs deployed.

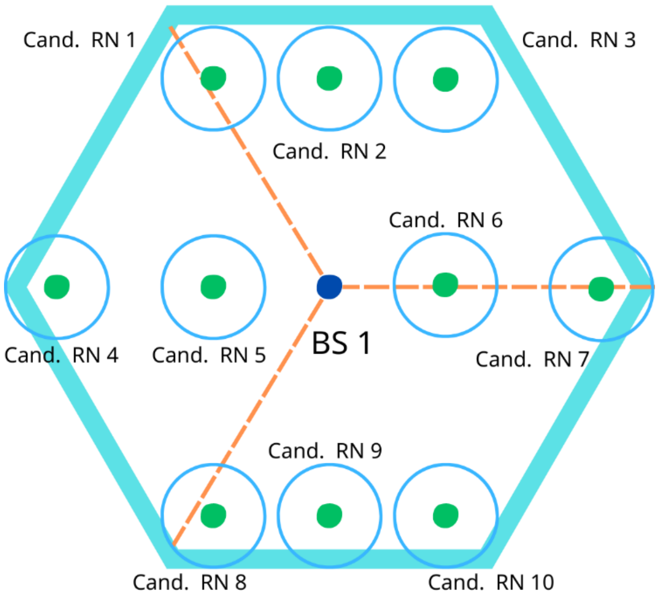


Figure 0-2: 5G/B5G system's cell with candidate RNs

Thus, the N_{CRN} best-performing RNs are selected out of S_{rc}, where $S_{rc} = \{\mathrm{rc}_1, \mathrm{rc}_2, \dots, \mathrm{rc}_{\mathrm{RN_{can}}}\}$ is the set of candidate RNs is each cell, subject to the following constraints:

(C1) $\min(PL_n)$, $\forall n \in \mathbb{N}$, where PL_n is the pathloss between each accepted UE by the secondary system, and the RN that assigned to.

(C2) $min(P_{t,r}), \forall r \in \mathbb{R}$, where $P_{t,r}$ is the total transmitted power by each deployed RN.

(C3) $max(AN_r), \forall r \in \mathbb{R}$, where AN_r denotes the total accepted UEs served by RNs.

Two offline ML-enabled methods are proposed to solve the aforementioned problem utilizing DL principles and techniques, as will be presented in paragraph 5.3.3. Moreover, both methods are examined and their performance is evaluated in the following two scenarios:

- *Scenario 1*: The channel coefficient matrix sub-table is known for the link of each UE and the corresponding BS. Moreover, the channel coefficient sub-tables are known, also, for the RN-UE link.
- *Scenario 2*: There is no CSI information available both for the BS-RN and the RN-UE link. Thus, dataset construction and algorithms are based only on geographical, pathloss and topology parameters.

5.3.2 Dataset generation

A key procedure for building ML models is the validation and training stage. For this purpose, datasets used for learning objectives should be accurate, up-to-date and should always be evaluated. A MATLAB relay-assisted 5G/B5G link and system level network simulator is used to construct datasets after adequate Monte-Carlo (MC) simulation rounds. This simulator is based on the work in [CONF-1], where both different Inband and Outband A&F RN scenarios are considered (see also paragraph 1.3.3 for RN types). In fact the following scenarios are configurated in the aforementioned simulator:

1) *No-RN*: No RNs deployed,
2) Sector Mid Edge Inband *(SME-I)*: OnDemand–Inband RNs deployed in the middle edge of each sector,
3) *ANY-I*: OnDemand Inband RNs deployed wherever deemed necessary,
4) All Cell Edges Inband (*ACE-I*): OnDemand Inband RNs deployed at the edges of each cell and
5) Sector Mid Edge Outband (*SME-O*): Predefined Outband RNs deployed in the middle edge of each sector.

A significant aspect of this simulator that should be pointed out is the resource allocation (subcarrier allocation, user association to BS or RN) algorithm that is implemented. This algorithm aims to combine the MIMO and OFDMA principles with the RRM and RN-deployment processes, as a joint approach to improve EE and SE. All related parameters are presented in Table I, while the description is analyzed in Fig. 1.

Parameter	Variable
Number of SCs requested by the nth UE	R_n
Number of available SCs in each BS/Outband RN	N_{sc}/N_{rn-o}
Set of SCs allocated to the nth UE	S_n
Available SCs of the bth BS/ rth outband RN/cluster	$S_b/S_{rn-o}/S_{cl}$
Types – Classes of RNs (RNtype)	*No-RN*, Inband, Outband
Set of served UEs by the bth BS /rth RN	U_b/U_r
Total losses of the nth UE from BS or RN	$TL_{n,b}/TL_{n,r}$
Channel Matrix for the lth SC of the nth UE	$\boldsymbol{H}_{n,\mathrm{sec}(n),l}$
Power assigned to the lth SC of the nth UE	$p_{n,l}$
Maximum Tx Power per SC/BS or RN	$P_{t-sc,max}/P_{t-BS,max}$
Number of rejected UEs	UE_{rej}
SNR threshold level	SNR_{thr}

Table 0-1: RRM algorithm's parameters [CONF-1]

In **Step 1**, the available subcarriers per BS or RN are defined (i.e., S_b denotes the set of available subcarriers of the bth BS). Moreover, if relay-assisted transmission has been selected, the corresponding topology is formulated. In **Step 2**, BS selection for the nth UE takes place, according to pathloss minimization ($PL_{n,b}$ denotes the pathlosses of the nth UE with respect to the bth BS). Channel modeling is performed according to the latest 3GPP specifications [86], by integrating mobility parameters, existence of Line of Sight (LOS) propagation and outage probability estimation. In the same step, the available SCs per BS-UE link are defined as well. In our approach, RA is performed per cluster, i.e., per group of adjacent sectors. This approach is based on the Adjacent Sectors - Maximum SNR technique of [185]. To this end, each allocated SC is made unavailable for the other adjacent sectors. In case of lack of available SCs, the UE can be served by outband RNs.

Algorithm 1 Proposed Relay Assisted RRM Algorithm

Step 1: Set $S_b \leftarrow \{1 : N_{sc}\}, 1 \leq b \leq B, S_{cl} \leftarrow S_b,$
$S_{rn\text{-}o} \leftarrow \{1 : N_{rn\text{-}o}\}, U_b \leftarrow \{\}, U_r \leftarrow \{\},$
$UE_{rej} \leftarrow 0, n \leftarrow 0$
Step 2: $n \leftarrow n + 1, b \leftarrow \underset{1 \leq b' \leq B}{\operatorname{argmin}} \|PL_{b'}\|, S_n \leftarrow \{\}$
The n^{th} UE requests R_n SCs. Set $A_s \leftarrow S_b \cap S_{cl}$
if $|A_s| \geq R_n$ **then**
    $TL_n \leftarrow TL_{n,b}, U_b \leftarrow U_b \cup n, U \leftarrow U_b$
    Go to **Step 4**
else if $RN_{\text{type}} = Outband$ **then**
    $A_s \leftarrow S_{rn\text{-}o}$, check for the r^{th} RN in **Step 3**
else
    $UE_{rej} \leftarrow UE_{rej} + 1$, Go to **Step 2**
end if
Step 3:
if $|A_s| \leq R_n$ **then**
    $UE_{rej} \leftarrow UE_{rej} + 1$, Go to **Step 2**
else
    $TL_n \leftarrow TL_{n,r}, U_r \leftarrow U_r \cup n, U \leftarrow U_r$
end if
Step 4: $l \leftarrow \underset{j \in A_s}{\operatorname{argmax}} \|\mathbf{H}_{n,sec(n),j}\|_F^2,$
$\mathbf{t}_{n,l} \leftarrow \mathbf{x}(\lambda_{\text{m}}(\mathbf{H}_{n,sec(n),l}^H \mathbf{H}_{n,sec(n),l})),$
$G_{n,l} \leftarrow \|\mathbf{H}_{n,sec(n),l}\|_F^2 / TL_n \; p_{n,l} \leftarrow SNR_{thr} I_0 TL_n / G_{n,l}$
Check channel conditions and if possible change modulation level, increase SNR_{thr} and go to **Step 4**
Step 5:
if $(p_{n,l} \geq P_{t\text{-}sc,max})$ or $\left(\sum_{n' \in U} \sum_{l \in S_{n'}} p_{n',l} \geq P_{t\text{-}bs,max}\right)$ **then**
    if $RN_{\text{type}} = Outband$ **then**
        $UE_{rej} \leftarrow UE_{rej} + 1,$
        Go to **Step 2**
    else if $RN_{\text{type}} = Inband$ **then**
        $TL_n \leftarrow TL_{n,b} + TL_{n,r}, U_r \leftarrow U_r \cup n, U \leftarrow U_r$
        Recalculate $l, \mathbf{t}_{n,l}, G_{n,l}, p_{n,l}$
        if $(p_{n,l} \geq P_{t\text{-}sc,max})$ or
            $\left(\sum_{n' \in U} \sum_{l \in S_{n'}} p_{n',l} \geq P_{t\text{-}bs,max}\right)$ **then**
            $UE_{rej} \leftarrow UE_{rej} + 1, U_r \leftarrow U_r - n,$
            Go to **Step 2**
        else $S_{cl} \leftarrow S_{cl} - n, S_b \leftarrow S_b - l, S_n \leftarrow S_n \cup l$
            if $|S_n| < R_n$ **then**
                Go to **Step 4**
            end if
        end if
    end if
    if $RN_{\text{type}} = Outband$ **then**
        $S_{rn\text{-}o} \leftarrow S_{rn\text{-}o} - l$
    end if
    $S_{cl} \leftarrow S_{cl} - n, S_b \leftarrow S_b - l, S_n \leftarrow S_n \cup l$
    if $|S_n| < R_{\text{n}}$ **then**
        Go to **Step 4**
    end if
end if
Step 6: Calculate system KPIs

Figure 0-3: RRM algorithm [CONF-1]

In this event, the set of available subcarriers is updated in **Step 3**. The potential UE is rejected from the network, if it cannot be served by the outband RN due to lack of available subcarriers. Otherwise, in **Step 4**, subcarrier allocation takes place, based on the maximization of the impulse response of the channel. To this end, $\|x\|_F$ is the Frobenius norm of vector matrix x, while $x(\lambda_m(\boldsymbol{A}))$ is the eigenvector corresponding to the maximum eigenvalue of matrix $\boldsymbol{A}$. In this step, the achieved channel gain ($G_{n,l}$) for the l^{th} subcarrier of the n^{th} UE, as well as the required transmission power ($p_{n,l}$) for acceptable QoS, are calculated. In **Step 5**, power management is tackled. If power outage occurs in the outband scenario, the potential UE is rejected. Otherwise, if an inband RN scenario has been considered, then all parameters of Step 4 are recalculated. In the event of power outage, the potential UE is rejected, as done previously. In all cases, all relevant sets are updated. Finally, system's KPIs are calculated in **Step 6**.

The aforementioned simulator takes into consideration all physical layer aspects such as small and large scale fading, interference management and cluster definition for each user of interest, etc. However, the following improvements have been made for the dataset generation task:

- The deployment of more RNs per cell has been included. In [CONF-1] all scenarios (both Inband and Outband ones) consider the deployment of up to three RNs per cell, mainly deployed in cell edges. In the updated version of the 5G simulator, an increased number of RNs per cell is considered, so that the best performing RN can be selected for each accepted user in an unbiased manner.
- Moreover, channel modelling has been updated according to the newest 3GPP specifications (basically the latest version of 3GPP TS 138 211 regulation) by integrating mobility parameters, existence of Line of Sight (LOS) propagation and outage probability estimation [186].
- The Algorithm 1 (Fig. 5-3) is extended to select the best RN (out of the deployed ones in each cell) based on both minimum pathloss and energy consumption. Hence, this algorithm, which combines MIMO and OFDMA principles in two-hop

5G/B5G cellular orientations, tries to maximize both the EE and SE for the overall orientation under evaluation.

Such a topology is presented in Fig. 5-2 concerning 10 potential RNs. Thus, by performing numerous MC simulations we store the performance of various UEs, both indoor and outdoor ones, and both moving and static ones. Then, we are focusing only on the UEs that are served by the secondary system. MC simulations are finalized only after adequate UEs' performance is simulated. For the NP-Hard RN placement problem simulating 10000 to 100000 UEs defines an adequate number of UEs' performance evaluation. The values that are stored for each UE, which is accepted by the secondary system in the simulation round, concern both

location/localization parameters (x, y and z-axis position), serving BS, pathloss, total losses and MIMO parameters (channel coefficient matrix). All related variables and metrics of interest for each simulated UE are presented in Table 5-2, forming the dataset used for DL-model training.

Feature	Description
$\boldsymbol{UE_x}$	x-axis position of the UE
$\boldsymbol{UE_y}$	y-axis position of the UE
$\boldsymbol{UE_z}$	z-axis position of the UE
$\boldsymbol{BS_{serve}}$	ID of the BS that serves the UE (related to the RN to be selected)
$\boldsymbol{UE_{sec}}$	Serving sector of the UE
UE-BS_{angle}	Angle between BS and UE
PL_{mat}	$RN_{can} \times 1$ matrix with the Pathloss between the UE and all the potential RNs
TL_{mat}	$RN_{can} \times 1$ matrix with the Pathloss between the UE and all the potential RNs
$\mathbf{H}_{matrix}$	$M_r \times M_t$ channel matrix coefficient (used only in *Scenario 1*)
RN_{serve}	ID of the RN that serves the UE (**response variable**)

Table 0-2: Dataset Features

Thus, the whole dataset feature number is the following:

$$Datasetsize = \begin{cases} 6 + 2 \times RN_{can} + M_r \times M_t, Scenario\ 1 \\ 6 + 2 \times RN_{can}, Scenario\ 2 \end{cases} \quad (15)$$

5.3.3 Deep Learning Algorithm for Relay Node Placement

Using the dataset that has been analyzed in paragraph 5.3.2, two DL models are proposed to predict the best performing RN for the UEs of the secondary system. It should be noted that for hyperparameter tuning and selection the Exhaustive Grid Search method has been utilized in both models' design [31]. According to that method multiple search rounds are performed over all possible hyperparameter configurations in order for the best performing ones to be selected based on the KPIs of interest (in this case accuracy and F1-score). The next two subparagraphs depict the proposed DL models for the RN placement problem in 5G.B5G networks. The first model considers a DNN architecture, whereas the second model considers a LSTM one,

5.3.3.1 Deep Neural Network

The structure of the proposed DNN is the following, as also depicted in Fig. 5-4:

- Feature input later with z-score normalization of the input, where $Dataset_{size}$ features are inserted to the DNN.
- A fully connected layer with 50×1 output size, multiplies the input (feature input layer) by the corresponding weight matrix and, also, adds the bias vector.
- A batch normalization layer, to normalize data across all observations for each channel independently, making training of the NN faster through re-centering and rescaling.
- A ReLU layer, using rectified activation function to force the input directly to the output if it is positive, otherwise, to zero output.
- Another, fully connected layer similar to the previous one with output size $num_{Classes} \times 1$, where $num_{Classes} = RN_{can}$.
- A soft maximization (sofmax) layer to predict the multinomial probability distribution of the data. These layers are commonly used in multi-class classification tasks, as the one that is examined in this work.
- The classification's output layer, which produces the predicted best-performing RN for each UE.

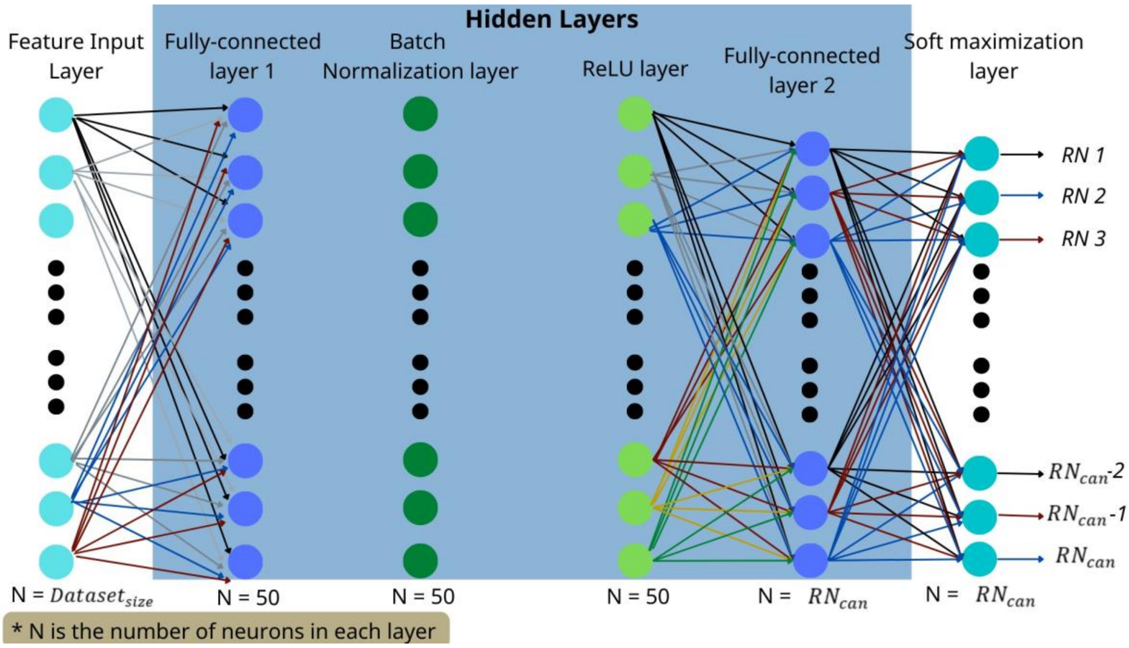


Figure 0-4: Proposed DNN's structure for RN placement

5.3.3.2 Long-Short Memory Network

The second proposed DL algorithm considers a Recurrent NN (RNN), LSTM, with the following structure (as also depicted in Fig. 5-5):

- Feature input layer with z-score normalization of the input, where $Dataset_{size}$ features are inserted to the DNN.
- An LSTM layer with 52 hidden units. This layer is categorized as an RNN layer, which learns long-term dependencies between data features. Additive interactions between features are used to improve gradient flow over long sequences of data throughout training phase.
- A dropout layer with 0.2 probability to randomly set input elements to zero.
- Another LSTM layer with 40 hidden units.

- Another dropout layer, as the previous one.
- Another LSTM layer with 15 hidden units.
- Another dropout layer, as the previous ones.
- A fully connected layer like the previous one with $num_{Classes} \times 1$, where $num_{Classes} = RNcan$.
- A soft maximization layer.
- The classification's output layer, which produces as output the predicted best-performing RN for each UE.

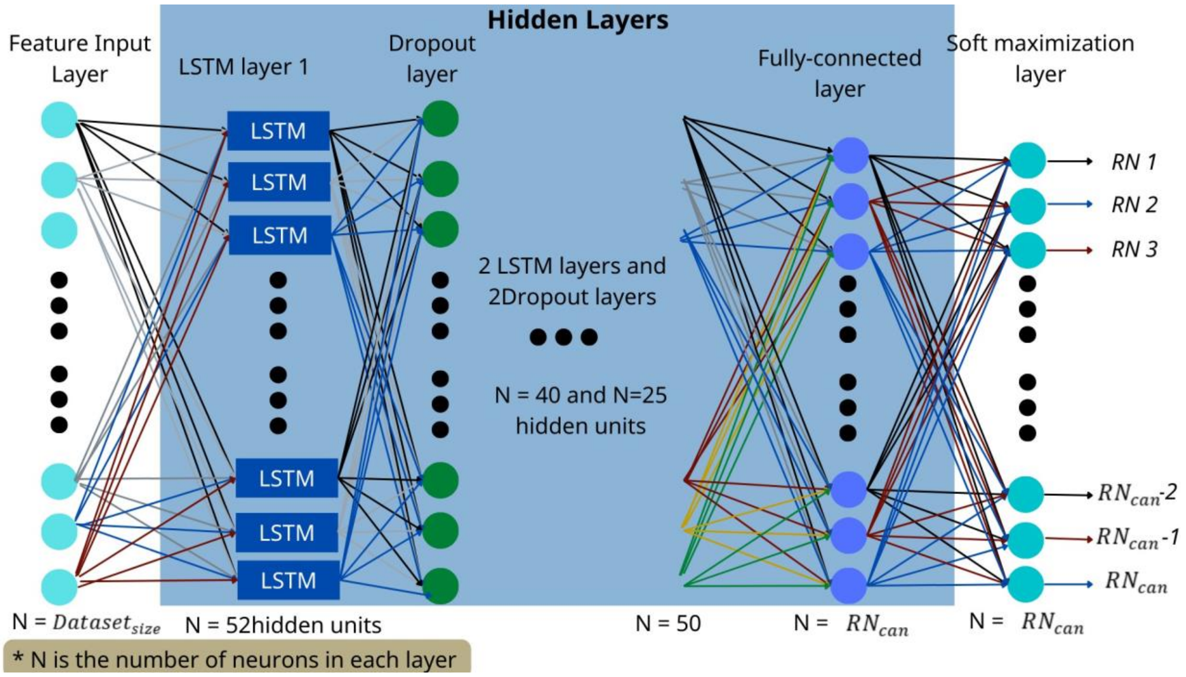


Figure 0-5: Proposed LSTM network's structure for RN placement

5.3.3.3 Result Evaluation

The downlink of a wireless multicellular 5G orientation is considered, where extensive use of RNs takes place. A 2-tier and 19 cell topology is of interest, where UEs are uniformly distributed. Concerning the used MIMO antenna configurations, both BSs, RNs and UEs are equipped with 2 antennas. Each BS's antenna lays at 25 m, while each RN's one lays at 12,5 m and each UE's one at 1,5 m. The relevant antenna gains are 18/9/4 dB for BSs, RNs and UEs respectively. Each accepted UE requests 6 subcarriers in each timeslot, while 132 subcarriers are available to be allocated to UEs from each BS. Subcarrier spacing is set to 60 kHz. A significant configuration parameter is the possibility of direct LOS connection between BSs - UEs, BSs- RNs and RNs-UEs. The first two parameters are defined by [30], while the RN-UE LOS existence, which is not regulated, is set to 10%.

The performance of a large number of UEs (50.000 indoor/outdoor -with 80/20% probability- moving/static UEs) is simulated to construct the dataset used for training of our DL models. Moreover, 10 candidate RNs are deployed in each cell's coverage area, as shown in Fig. 2. An adaptive modulation scheme is used based on each UE's demands for QoS levels. Three different modulation levels (QPSK,16-QAM and 64-QAM) are considered along with their

respective threshold values. All simulation parameters are summarized in Table 2.

Parameter	Value/Assumption
Tiers/Number of	2/19
Carrier frequency	28 GHz
Simulated UEs	50.000
Number of antennas per BS/RN/UE	2/2/2
Cell radius	500√ 3=288.68 m
BS antenna height	25 m
UE antenna height	1.5 m
Indoor to Outdoor UE ratio	80%/20%
LOS BS-UE(RN-UE)/BS-RN Probability	[86] Table 7.4.2-1/10%
cells Maximum allowed pathloss (dB)	320
Antenna gains BS/RN/UE in dB	18/9/4
Number of requested subcarriers per UE	6
Number of subcarriers per BS or Cluster	132
Subcarrier spacing	60 kHz
SNIR threshold levels QPSK/16-QAM/64-QAM	[86] 9.6/16.4/22.7 dB

Table 0-3: Dataset Simulation Parameters

Using the parameters presented in Table 5-3, the MATLAB 5G/B5G system and link level simulator produces the dataset that is used as input to the two proposed DL models. During the training phase of both DL-based approaches, an 80%-20% training-test set split has been used, as well as a 10-fold cross validation procedure to split the dataset into training, validation and test set. The problem of optimal RN placement is examined as a classification one, by selecting the best performing RN out of the 10 potential RNs for each UE. The performance of the abovementioned classifiers is evaluated, using the accuracy and F1-score metrics.

Tables 5-4 and 5-5 summarize the performance of the two proposed DL models in the RN placement based on test set classification accuracy, precision, recall and F1-score for both *Scenario 1* and *Scenario 2*.

DNN	*Scenario 1*	*Scenario 2*
Accuracy	0.9260	0.9387
Precision	0.9251	0.9343
Recall	0.8951	0.9194
F1-score	0.9099	0.9268
Training time (s)	**4 min. 13 s.**	**3 min. 30 s.**

Table 0-4: DNN's performance

LSTM	*Scenario 1*	*Scenario 2*
Accuracy	**0.9513**	**0.9660**
Precision	0.9321	0.9618
Recall	0.9259	0.9502
F1-score	0.9290	0.9560
Training time (s)	4 min. 53 s.	5 min. 12 s.

Table 0-5: RNN's (LSTM's) performance

As it can be observed from Tables 5-4 and 5-5 LSTM algorithm’s performance is better that DNN’s performance (both accuracy, precision, recall and F1-score) when CSI is known and is included in training set’s features. Similarly, LSTM algorithm’s performance is better (both concerning accuracy, precision, recall and F1-score) when there is no CSI knowledge.

However, when fast, low-latency responses are considered in 5G/B5G networks, it is vital to examine the trade-off between ML metrics and training time required. In that perspective, it is visible from both Tables 5-4 and 5-5 that LSTM networks need some more time to train relative to DNNs. However, comparing training times of these two approaches (LSTM, DNN), we can state that training times are similar in both *Scenario 1* and *Scenario 2*. Thus, it is fair to say, that the overall performance of the LSTM networks is better than DNN, concerning ML/DL performance and metrics-training time trade off. The same conclusions can be drawn from Fig. 5-6 as well, where the accuracy and loss versus training epochs are displayed both for DNN and LSTM algorithms in the two examined scenarios.

After evaluating the two proposed DL models (ANN, RNN) based on the ML classification KPIs, we use these two approaches to identify the k best performing RNs out of the 10 candidate active ones placed in each cell of the topology (see Fig. 5-2). This is achieved using our lab's MATLAB 5G/B5G link and system level network simulator, as follows:

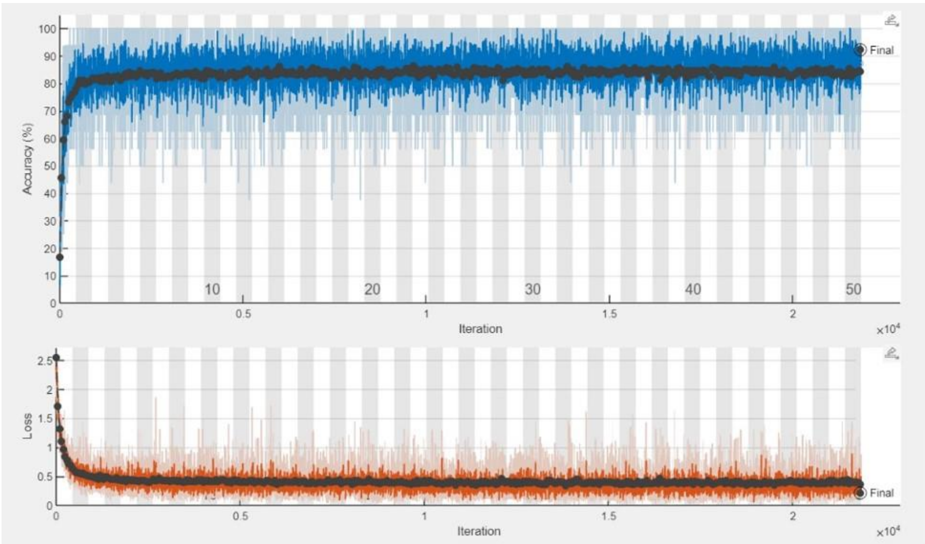
- Simulate the performance of 100000 UEs in the cellular topology of Fig. 5-2, configured with the parameters in Table 5-3.
- Select the best-performing RN for each UE using the two proposed ML/DL models, both in *Scenario 1* and *Scenario 2*.
- Find the k potential RNs serving the most UEs, and thus, assign them as deployed ones. The proposed models are evaluated with $k = 3$ deployed RNs in each cell of the

cellular topology.

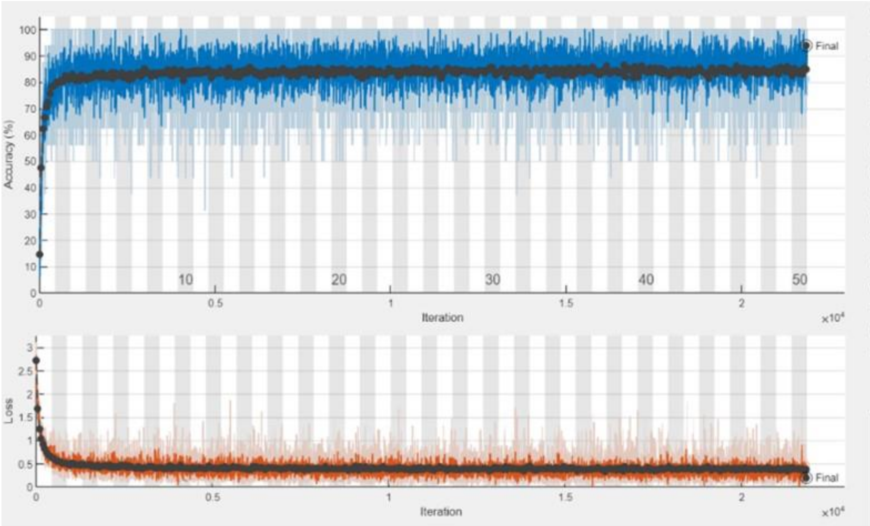
Table 5-6 presents the k=3 best-performing RNs out of the 10 potential ones, that are selected to be deployed in each cell of the cellular topology illustrated in Fig. 5-2, which is also used in overall system's performance evaluation.

Rank	*Scenario 1*		Scenario 2	
	DNN	RNN	DNN	RNN
1	RN-10	RN-10	RN-10	RN-10
2	RN-6	RN-6	RN-6	RN-6
3	RN-5	RN-5	RN-5	RN-4

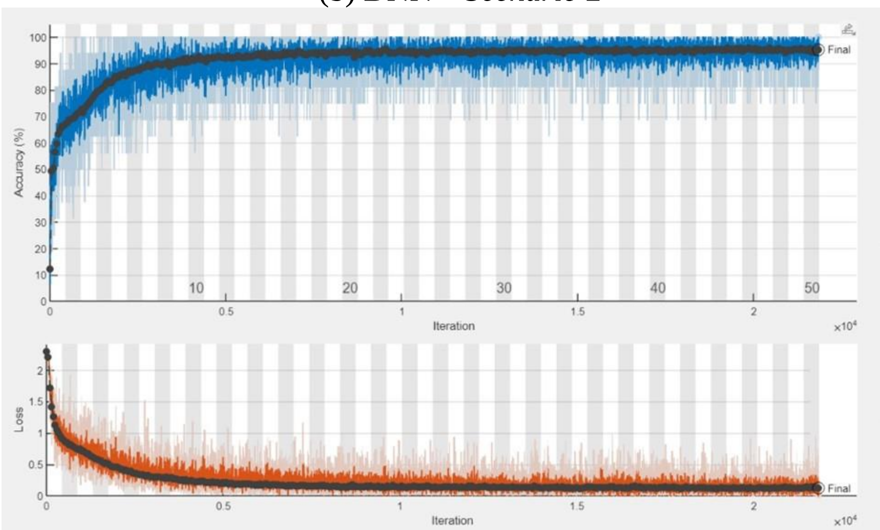
Table 0-6: Deployed RNs after performance evaluation



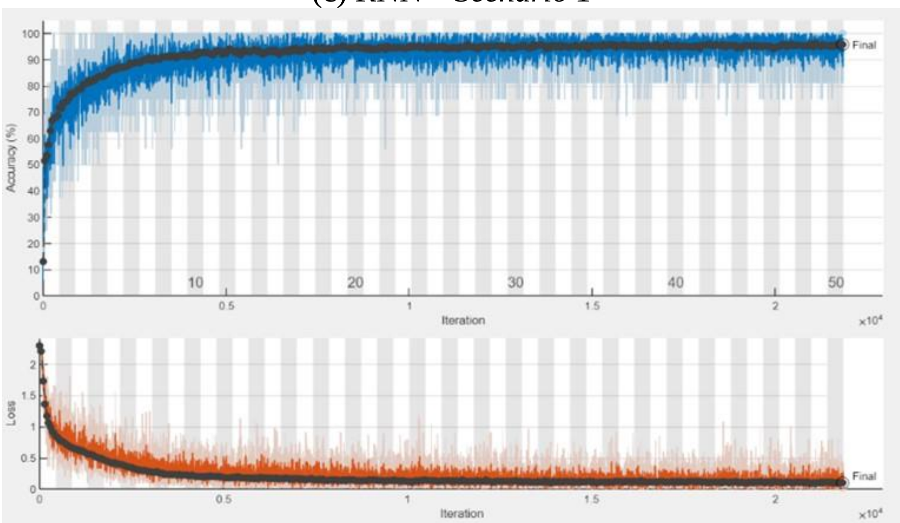
(a) DNN-*Scenario 1*



(b) DNN – *Scenario 2*



(c) RNN – *Scenario 1*



(c) RNN – *Scenario 2*

Figure 0-6: Accuracy and Loss per training iteration and epoch

5.3.4 Distributed Learning for Relay Node Placement

5.3.4.1 Proposed Federated Learning scheme for Relay Node Placement

Due to the increasing needs of 5G/B5G/6G networks UEs for interrupted access to the medium, low latency and QoS flows continuity, the need for splitting the computation overload in these dense network environments arises. For this purpose a DL model (similar with the one presented in paragraph 5.3.3.1) is trained and evaluated both by a CL-enabled training algorithm and, also, by an FL-one.

For the RN selection task, the LSTM network which is used, has the following structure:

- Feature input layer with z-score normalization of the input, where the different features are inserted into the DNN.
- An LSTM layer with 52 hidden units
- A dropout layer with 0.2 probability to randomly set input elements to zero.
- Two sets of LSTM layers followed by a dropout layer. The first LSTM layer has 40 hidden units, while the latter has 15 hidden units.
- A fully connected layer with an output size equal to the number of candidate RNs.
- A soft maximization layer.
- The classification's output layer, which produces as output the predicted best-performing RN for each user. Thus a number from 1 to N is the output of the model, which signifies the selected RN for each user.

5.3.4.2 CL and FL model training

Aiming to demonstrate the advantages of the FL over CL approaches, we consider two different training topologies for the problem of RN placement in B5G (6G) networks. These are the following:

a) **CL-based approach**: In the first approach all the training is performed in the centralized entity. The centralized entity in this occasion is the cell's BS, which receives the data gathered in the wireless environment by the RNs. Afterwards, the global dataset is formed and the DL model is trained in a centralized manner.

b) **FL-based approach**: In this approach, the data gathered in the wireless environment train local models located in each of the R RNs of the wireless topology. Thus, local models are trained and parameters are transmitted in the centralized entity (BSs) to be optimized according to the implemented federated averaging function.

5.3.4.3 Result Evaluation

We consider the downlink of a wireless B5G (6G) orientation, where extensive use of RNs takes place. The topology under test considers one BS and 10 RNs, where users are uniformly distributed. We simulate the performance of a large number of total users (50.000 indoor/outdoor moving/static) to construct both the global dataset for the CL case and the local datasets for the FL case. During the training phase of both approaches, an 80%-20% training-test set split is performed, as well as a 10-fold cross-validation procedure to split the dataset into training, validation, and test set. The 10-fold cross-validation splits the training set into ten parts where, in each case, nine of them are used for training and the remaining one for validation.

The problem of optimal RN placement is examined as a classification one, by selecting the best-performing RN out of the 10 potential RNs for each user. The performance of the abovementioned approaches is evaluated both concerning ML KPIs (accuracy, precision, recall, F1-score) and based on the total training latency.

Table 5-7 and Table 5-8 summarize the performance of the two approaches (CL, DL) in the RN placement based on test set classification accuracy, precision, recall and F1-score for both Scenario A and Scenario B, respectively.

LSTM	Scenario A	Scenario B
Accuracy	0.9513	0.9660
Precision	0.9521	0.9618
Recall	0.9259	0.9502
F1-score	0.9290	0.9560
Training time	5 min. 15 sec.	5 min. 50 sec.

Table 0-7: LSTM performance - CL scenario

LSTM	Scenario A	Scenario B
Accuracy	0.9107	0.9309
Precision	0.9259	0.9346
Recall	0.8929	0.9259
F1-score	0.9091	0.9302
Training time	1 min. 35 sec.	1 min. 58 sec.

Table 0-8: LSTM performance - FL scenario

As can be observed from Tables 5-7 and 5-8 LSTM's performance is better (both accuracy, precision, recall and F1-score) when CSI is known and is included in the training set's features. Moreover, it can be seen that training times are similar both for Scenario A and Scenario B.

However, when fast, low-latency responses are considered in B5G (6G) networks, it is vital to examine the trade-off between ML metrics and the training time required. In that perspective, it is visible from the aforementioned tables (Tables 7 and 8) that the FL-based approach worsens slightly all the ML-related networks KPIs (accuracy, precision, recall, F1-score) by ~5% compared to the CL approach. However, this degradation can be characterized as small enough relevant to the gain in the total training time of the FL approach compared to the CL one. In fact, the gain in this metric (total training latency) is about ~70% to ~75%.

5.3.4.4 Outcomes – Discussion over CL vs FL

Concerning the aforementioned comparison between CL and FL implementation for the RN placement problem in 5G/B5G network, but, also, concerning the literature presented in Section 3, it is visible that FL is of primary interest in 5G, but especially in B5G (6G) orientations, to enhance the potential PHY gains and, also, support the growing user requirements. However, several challenges have to be addressed for the feasibility of such approaches. These can be summarized as follows (see also Table 5-9):

- **Distributed training and Models' scalability**: In B5G networks interconnected devices number is growing, resulting in the densification of the networks. However, the processing units and the computational power of these devices may be limited. Thus, a key challenge that the proposed FL schemes have to consider is the training time required and the efficient allocation of the total computational resources.

- **Secure communication and device-to-centralized entity transmissions**: By definition FL secures local datasets, as only model parameters transmission is performed to the centralized entity. However, challenges exist in the transmission of models parameters, where information may be vulnerable to eavesdropping capable of reconstruction.
- **Non-IID data**: As is already pointed out, the different users devices connected to 6G networks, that perform FL training have different characteristics concerning processing and computational power, battery life etc. This heterogeneity, affects parameters such as convergence time, training latency, and others.
- **Computation and communication trade-off:** The goal of an effective and efficient FL mechanism is twofold. On the one hand, the communication links and uninterrupted interconnection between the enrolled devices should be present, while, on the other hand, computational complexity and total training times should be minimized as possible.

Challenge	Solutions presented at
Distributed learning computational and scalability considerations	[136], [140], [141], [145]
Security and Privacy concerns	[188], [189], [190]
Non-IID data	[137], [188]
Computation and communication trade-off	[132], [147], [137]

Table 0-9: Challenges in FL models construction in 5G/B5G wireless networks

5.4 RN Selection in 5G/B5G Networks

5.4.1 Problem Formulation

As depicted in Fig. 5-7, for each cell of the cellular topology, there is a M_t antenna source -which is located at the BS of each cell, $N_{u_{RN}}$ UEs -where $N_{u_{RN}} \leq N$ are the initially rejected UEs from the primary system, that request RN assistance, equipped with M_r antennas, and N_{CRN} RNs in the two-hop wireless relay network. If a UE is initially rejected, the direct link between source and destination does not exist due to high pathloss effect. Therefore, A&F relays are used to process the received signal and support communication. Each UE is connected only to one RN and orthogonal channels are used to achieve full set gain and mitigate co-channel interference. This sub-problem's goal is to optimally select the most suitable RN out of the N_{CRN}candidate ones for each UE $n \epsilon N_{u_{RN}}$, with respect to the active user maximization for each cell of the topology.

In a two-hop 5G/B5G wireless communications system, like the one depicted in Fig. 5-1, the total bandwidth, BW, is divided into N_{sc} subcarriers to be allocated to the accepted UEs. There are two classes of accepted UEs. On the one hand, the first class contains UEs that are directly accepted by the primary system (BS-UE direct communication). The SNIR for the n^{th} UE ($1 \leq n \leq N$) of this category, associated with the l^{th} subcarrier ($1 \leq l \leq Nsc$) for a specific channel realization and assuming independent BS-UE links, is given by equation (5).

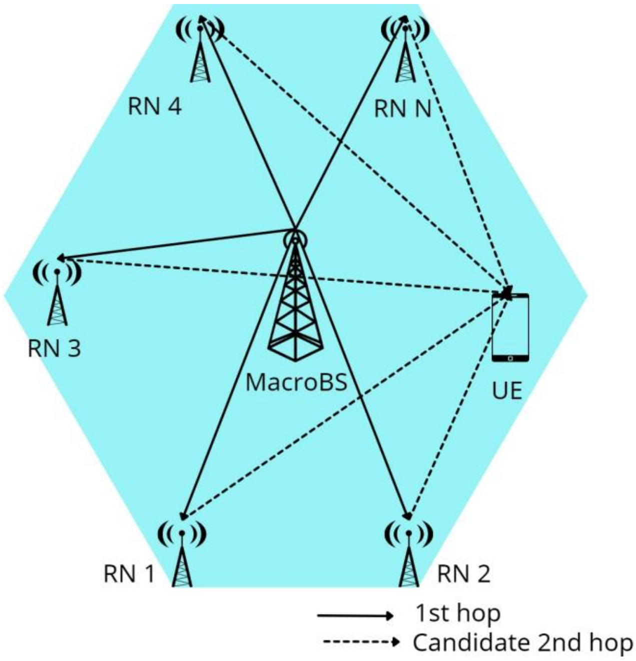


Figure 0-7: Two-hop 5G/B5G Relay Selection

On the other hand, the second class contains UEs that are directly connected to the secondary system (RN-UE connection). Thus, through relaying, BS-UE communication link is established through multi-hop communication. In this two-hop connection between BSs and UEs, RNs can be defined as UEs in the BS-RN link, and as BSs in the RN-UE link. In this case, for the nth UE ($1 \leq n \leq N$) of this category equation (5) is modified as follows:

$$SNIR_{n,l}(RN) = \frac{G_{n,n,l}(RN-UE)}{r_{n,l}^{H} r_{n,l} I_0 + I_{BS_{n,l}} + I_{RN_{n,l}}} \quad (16)$$

Where $I_{BS_{n,l}} = \sum_{b=1}^{N_{BS}} \sum_{m\epsilon UE_b, l\epsilon S_m} G_{n,m,l}$ and $I_{RN_{n,l}} = \sum_{b=1}^{N_{RN}} \sum_{j\epsilon UE_r, l\epsilon S_j} G_{n,j,l}$ are the cumulative interference levels for the lth subcarrier of nth UE served by the bth BS or rth RN. Moreover, N_{BS}, N_{RN} are the total number of BSs and RNs in the topology, respectively, UE_r denotes the set of UEs served by the rth RN, while the notation x-y indicates all possible link connections.

In this occasion, the total system throughput is given by [191] for the whole two-hop wireless communication 5G/B5G system:

$$R = \sum_{n=1}^{N} \sum_{s\epsilon S_n} r_{n,s} = B_{sc}\{\sum_{b=1}^{N_{BS}} \sum_{n\epsilon UE_b} \sum_{s\epsilon S_n} \log_2\left(1 + SNIR_{n,s}(BS)\right) + \sum_{b=1}^{N_{RN}} \sum_{m\epsilon UE_r} \sum_{s\epsilon S_m} \log_2\left(1 + SNIR_{m,s}(RN)\right)\} \quad (17)$$

where $|S_n|$ indicates the length of the set S_n, $r_{n,s}$ is the corresponding data rate for the sth subcarrier and B_{SC} is the bandwidth per subcarrier. EE and SE for the overall system are defined be replacing (17) into (7) and (8) (see paragraph 3.1.1) accordingly.

A DQL scheme is proposed in the next paragraph to solve the aforementioned problem of selecting the suitable RN for each accepted UE of the secondary system. DQL extends the classic frameworks by utilizing ANNs to help software agents to learn how to define actions and rewards. In other words, a DQL framework optimizes underlying function approximation by the use of one (or sometimes two) ANNs to map states and actions to the rewards they lead to. Consequently, it is visible that such an approach can be quickly and dynamically adjustable based on the environment. In our case, the next paragraph proposes a dynamic DQL framework to select the best performing RN -out of the available ones- for each UEs of the secondary (RN-assisted) 5G/B5G system.

5.4.2 Deep Reinforcement Learning Framework for RN selection

5.4.2.1 Proposed DQL algorithm for RN selection

RL, as also analyzed in paragraph 2.2.3, is based on the interaction and communication with the learning environment to train and validate effective models, using a learning entity called software agent [J-1]. One of the most significant RL algorithms is the Q-Learning algorithm, which has been proposed as an efficient way to deal with rapidly changing and non-linear environments, as the one depicted in the RN selection problem formulation in the previous paragraph. However, because of the increased complexity of the aforementioned RRM problem due to the large set of potential actions, states and rewards needed in a Q-Learning framework when considering dense 5G/B5G networks, a NN can be trained to map the set of states with the best-performing action or in other words to perform the Q-function approximation. This RL technique is called DQL and fits perfectly in multi-dimensional problems, such as RN selection.

There are several DQL schemes, which are classified according to the algorithm's calculative iterations. The first category is the centralized DQL schemes, where a single software agent is used to perform the information gathering and processing from different sources placed in the environment.

In the wireless communications domain, such an agent can be placed to the core network or on a server in a BS and collect information from different BSs and/or RNs. The other category is the decentralized DQL schemes, where multiple software agents are utilized and each one of them is responsible for communication and information gathering from a specific subset of the overall environment. Such agents can be placed in different BSs and/or be responsible for a subset of the total accepted users in the topology.

The proposed DQL framework of this thesis considers a semi-centralized DQL framework is proposed to solve the RN selection problem subject to EE and SE maximization. The term semi-supervised, refers to the presence of multiple similar agents, one in each BS/cell of the topology.

The general state, action and reward of the proposed scheme are defined as follows:

State space: Assuming that there are E number of episodes for DQL agent training, the system state is described as $S = \{S_1, S_2, \dots, S_E\}$. At any time step, assuming t, the state is described by the following information about each UE, denoted as u, served by the secondary system (RN-assisted communication): a) the ID of the BS which serves UE u, b) the cell sector where UE u is positioned, c) the set of CSI information (channel coefficient matrices) between each one of the active RNs in the cell where UE u is located, declared as $H_u = \{H_{u,r_1}, H_{u,r_2}, \dots, H_{u,r_k}\}$, where k is the total number of active RNs in the considered cell.

Action space: The taken actions in each one of the E algorithm's episodes are noted as $A = \{A_1, A_2, \dots, A_E\}$. At any time step, assuming t, and assuming that the k_s, $k_s \in (1, 2, \dots, k)$ RN is currently selected for a UE u, the software agent can select the next, the previous or the same RN as the next action. In other words, the action that is taken at time t is denoted as $A_t = [a_{1,u_1}, a_{2,u_2}, \dots, a_{u,u_u}, \dots, a_{N,N}]$, where N denotes the total number of UEs that are served by the secondary system, $a_{m,u_m} \in \{RN_{step}, -RN_{step}, 0\}$ is the selection of the serving RN for UE m and $RN_{step}$is the change of RN for each UE under test. Thus, the serving RN update rule for each episode for UE m is calculated as follows:

$$RN_{m,u_m}(t) = RN_{m,u_m}(t-1) + a_{m,u_m}(t)(18)$$

Reward: After taking an action, as described previously, the DQL system transits into a new state thus leading to alternate RN selection for the UEs of the secondary system.

The feedback received at time t focuses on EE and SE levels maximization and is expressed by:

$$r_t = \{r_{t_{EE}}(S_{t-1}, A_{t-1}), r_{t_{SE}}(S_{t-1}, A_{t-1})\}(19)$$

Where,

$$r_{t_{EE}}(S_{t-1}, A_{t-1}) = \begin{cases} \frac{EE_t - EE_{t-1}}{EE_{t-1}} \times 100, & if\ EE_t > EE_{t-1} \\ 0, & otherwise \end{cases} \quad (20)$$

$$r_{t_{sE}}(S_{t-1}, A_{t-1}) = \begin{cases} \frac{SE_t - SE_{t-1}}{SE_{t-1}} \times 100, & if\ SE_t > SE_{t-1} \\ 0, & otherwise \end{cases} \quad (21)$$

Regarding the action selection strategy, the ϵ-greedy method is used to balance the DQL algorithm's exploration and exploitation phases (with probabilities ϵ and $1-\epsilon$ respectively). Exploration refers to the DQL phase of improving knowledge about each action, whereas exploitation refers to the phase of maximizing the reward function by exploiting the set's action-value estimation.

Fig. 5-8 depicts the proposed semi-centralized DQN algorithm, where one agent is deployed per cell/BS. Each agent's training is performed only for the coverage area of the cell that is located into. This means that each agent is responsible only for a subject of the total UEs of the network. Thus, this approach considers C (performance evaluation considers $C = 19$) DQL agents, equal to the total cells of the topology. Each DQL agent optimizes performance in the coverage area assigned to the BS that is located. In order to ensure the global (for all cells) optimization of EE and SE performance, a global reward is defined for the whole cellular topology by the addition of all the single rewards of the C deployed agents.

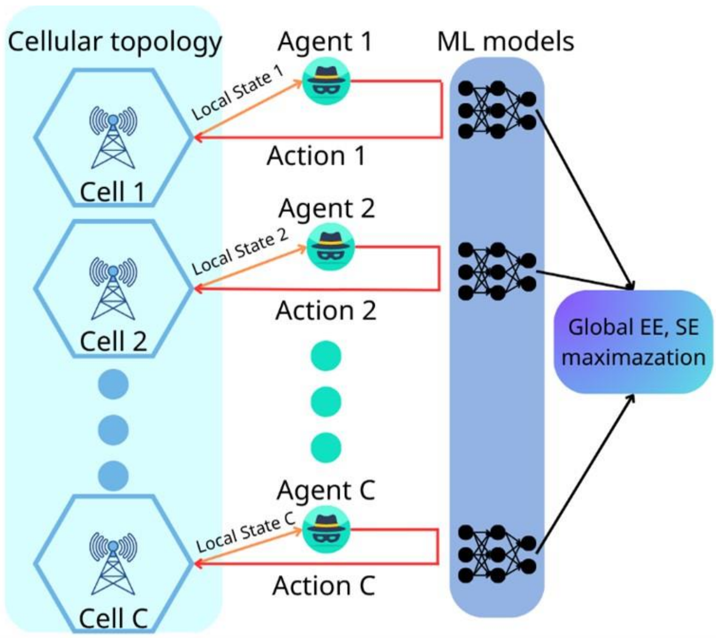


Figure 0-8: Proposed DQL scheme

To conclude with the DQL model, the global reward-based state transition is performed by a set of similar NNs, where the input layer includes the space state's triplet (serving BS ID, sector and channel coefficient between each UE of each cell and active RNs in a cell) for each of the C different agents (thus the corresponding BSs). The NN includes $C \times N_c \times 3$ neurons, where N_c is the number of active secondary system UEs in the cell $c \in C$. The output layer is one of the three possible Q-value results for each UE (select the next RN, select the previous RN or select the same RN) concerning system's EE and SE maximization. Afterwards, a global reward optimization step is performed in order to define if the total system will change state or not. The NN structure is depicted in Fig. 5-9.

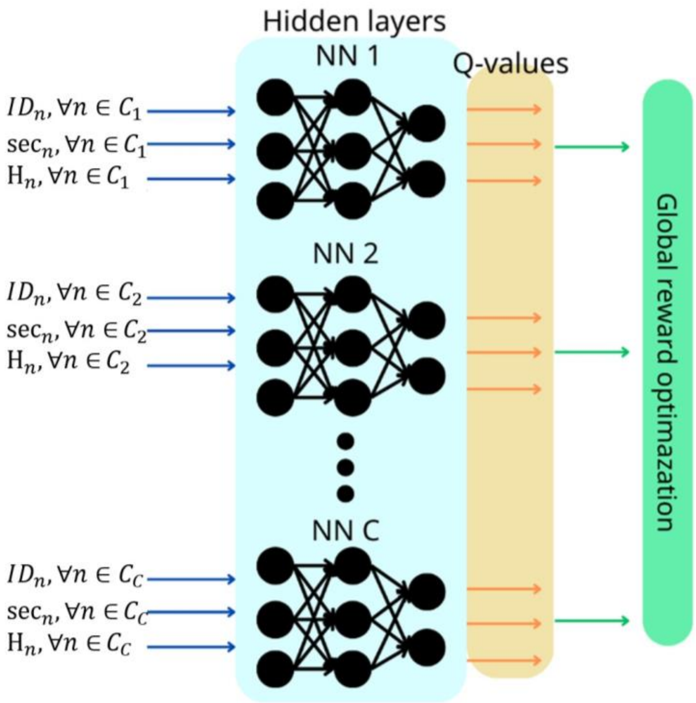


Figure 0-9: Proposed NNs architecture

5.5 Performance evaluation Evaluation

In this paragraph, the performance of the proposed ML algorithms for RN placement and selection is presented and evaluated concerning the downlink of a 2-tier wireless multicellular 5G/B5G orientation. In all cases, algorithms' performance is compared to a state-of-the-art non-ML approach, presented in [CONF-1], as well as to a reference system where no RNs are deployed. The deployed RNs are layer 1 RNs (A&F) regarding the OSI level of deployment. Both Inband and Outband RNs are considered. When Inband RNs are used both BS-RN and RN-UE links share the same spectrum resources. On the other hand, when Outband RNs are used, additional spectrum resources are -a priori- exclusively for RN usage [192].

All the simulation setups in this section were implemented in MATLAB (R2022b release [193]) environment using among others the Communications Toolbox, the Statistics and Machine Learning Toolbox and Deep Learning Toolbox.

This section is spitted in two subsections. The first refers to the performance evaluation of the ML/DL-based RN placement algorithm in different RN implementation scenarios. The second subsection, refers to the performance evaluation of the overall system, where both the ML/DL-based RN placement scheme and the DQL RN selection algorithm are deployed.

5.5.1 DL-based RN placement performance evaluation

In this subsection, the two proposed DL-schemes (DNN, LSTM), that have been presented in paragraph 5.3.3.1 for the problem of RN placement are evaluated. A 2-tier (19 BSs, 54 sectors) cellular orientation is considered, with network and simulation parameters as depicted in Table 5-3. UEs are uniformly distributed in the coverage area, while the number of requested subcarriers varies to either 6, 8 or 11.

Regarding RN implementation, five scenarios are examined in our simulations (including reference basis of no RN deployment), as follows: (1) *No-RN*: No RNs are deployed, (2) *SME-I*: Inband RNs are deployed in the middle edge of each sector, (3) *SME-O*: Outband RNs are deployed in the middle edge of each sector, (4) *MLP-I*: ML/DL-based Inband RN placement, (5) *MLP-O*: ML/DL-based Outband RN placement. It should be noted that in the aforementioned simulation environment Outband RN scenarios use an additional bandwidth of ~55MHz to serve initially rejected UEs, leading to interference mitigation and increased capacity gains over Inband ones [CONF-1]. It should be also noted that as LSTM's performance is slightly improved compared to DNN's performance, as depicted in section IV, we pick LSTM as the implemented ML/DL technique for RN placement for the simulations of this section.

Extensive MC simulations were performed, where the extracted mean values are presented for all considered KPIs. To this end, total system's EE is presented in Fig. 5-10, while the corresponding SE is presented in Fig. 5-11 for the aforementioned RN implementation scenarios. It should be noted that the best-performing candidate RNs are the same for the two scenarios that are discussed in section IV (CSI presence or not).

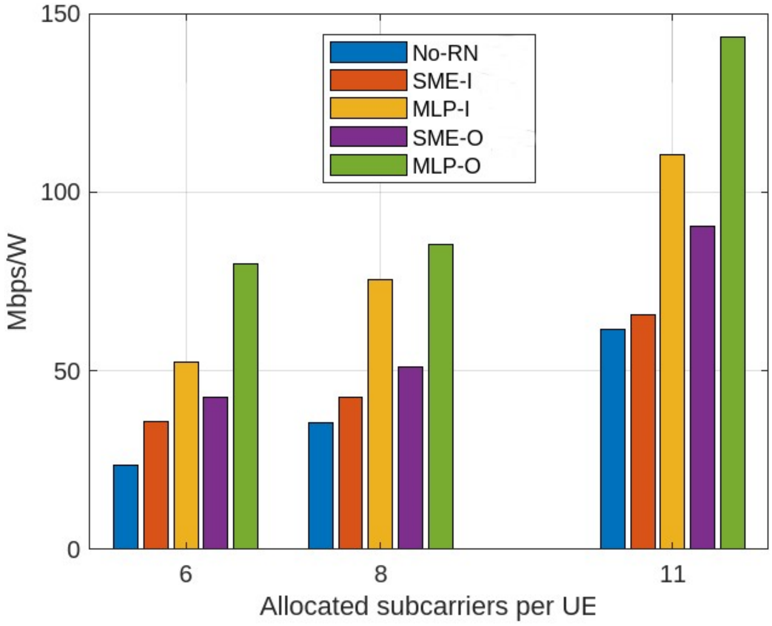


Figure 0-10: Mean total EE for various RN implementations

As it can be observed from Fig. 5-10, the use of RNs can significantly improve network's metrics, such as EE. Moreover, EE is increasing for increasing number of subcarriers per UE. In fact, for 6 subcarriers per UE, EE can reach up to 35.45/61.45 Mbps/W for the SME-I/SME-O scenarios, respectively. The EE values for the DL-enabled scenarios are 42.54/79.89 Mbps/W for the MLP-I/MLP-O scenarios, respectively. In the reference No-RN scenario, EE is limited to 23.45 Mbps/W. These numbers indicate that RN usage can improve total system's EE from ~50-240%. When considering 11 subcarriers per UE the corresponding values are 52.38/75.34/110.34/90.45/143.45 Mbps/W for the No-RN/SME-I/SME-O/MLP-I/MLP-O scenarios, respectively, which lead to a ~43-170% EE improvement. Similar conclusions can be drawn for SE as well, as depicted in Fig. 5-11, leading to a ~20-200% SE improvement.

It can be witnessed, also, from Figs. 5-10, 5-11 that the use of the DL scheme for RN placement further improves networks' KPIs, such as EE and SE. In fact, comparing the non-ML Inband scenario (SME-I) with the ML/DL-enabled Inband scenario (MLP-I), a ~20% improvement in both EE and SE for both 6 and 11 subcarriers per UE is depicted. Similarly, comparing the non-ML Outband scenario (SMEO) with the ML/DL-enabled Inband scenario (MLP-O), a ~30% improvement in both EE and SE for both 6 and 11 subcarriers per UE is achieved.

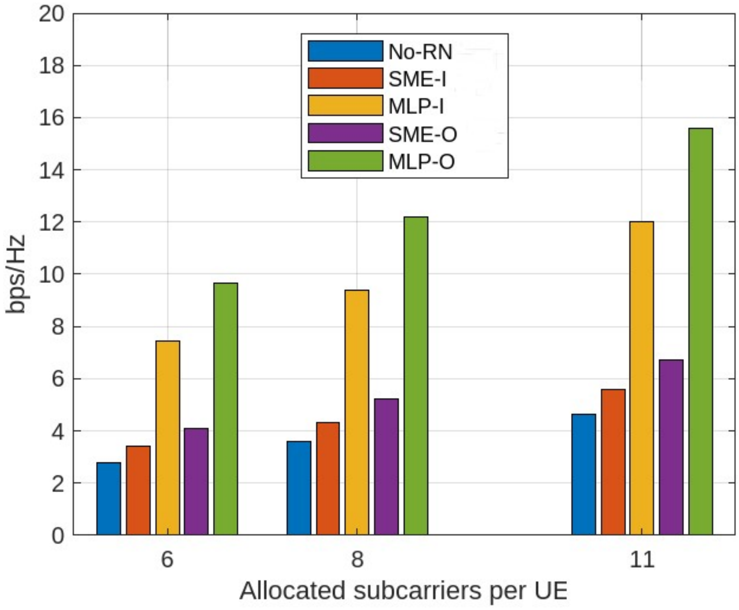


Figure 0-11: Mean total SE for various RN implementations

5.5.2 Overall performance evaluation (RN placement and Selection framework)

For the overall system's performance evaluation, the same 2-tier 5G/B5G network orientation as described in the previous subsection is considered, with the parameters depicted in Table 5-3. In this subsection the DQL scheme for RN selection, which is analyzed in paragraph 5.4.2.1 is, also, enabled, acting additively to the RN placement DL scheme presented in paragraph 5.3.3.1. The DQN parameters, that are used for the simulations of this subsection, are depicted in Table 5-10.

Parameter	Value	Component
Number of hidden layers	4	DQN
Activation function (input and hidden layers)	ReLU	DQN
Activation function (output layer)	Linear	DQN
Memory size	10000	DQN
Mini-batch size	128	DQN
Optimizer	Adam	DQN
Loss function	Huber	DQN
Number of episodes	40000	DQL
Learning rate ($\boldsymbol{\alpha}$)	0.001	DQL
Discount factor ($\boldsymbol{\gamma}$)	0.8	DQL

Table 0-10: DQN/DQL parameters

A key procedure that has to be performed when evaluating every ML-based scheme is hyperparameter tuning, which refers to extensive simulations with different ML parameter values. The scope of this procedure is the selection of the optimal set of parameters for the proposed ML schemes. These parameters are selected based on the overall system's performance optimization, based on KPIs of interest. The hyperparameters that have been selected after various simulations rounds are the following: a) number of episodes for the DQL algorithm, which affects the total training time, b) learning rate (α), which refers to the contribution percentage between the current and the previous Q-values, c) the discount factor (γ), which is linked to the significance of the future rewards.

As far as RN implementation is considered, five scenarios are examined in our simulations (including reference basis of no RN deployment), as follows: (1) *No-RN*: No RNs deployed, (2) *SME-I*: Inband RNs are deployed in the middle edge of each sector, (3) *SME-O*: Outband RNs are deployed in the middle edge of each sector, (4) *MLP-I*: ML/DL-based Inband RN placement and DQL RN selection, (5) *MLP-O*: ML/DL-based Outband RN placement and DQL RN selection.

To this end, total system's EE is presented in Fig. 5-12, while the corresponding SE is presented in Fig. 5-13 for the aforementioned RN implementation scenarios. As it can be observed from Fig. 5-12, the use of DRL-based RN placement can significantly improve network metrics, such as EE compared to the reference scenario where no RNs are deployed. In fact, for 6 subcarriers per UE, EE can reach up to 35.45/61.45 Mbps/W for the SME-I/SME-O scenarios, respectively. The EE values for the DQL scenarios are 76.95/139.79 Mbps/W for the MLP-I/MLP-O scenarios, respectively. In the reference No-RN scenario, EE is limited to 23.45 Mbps/W. These numbers indicate that DQL RN selection utilization can improve total EE from ~140-500%. When considering 11 subcarriers per UE the corresponding values are 52.38/75.34/110.34/166.35/252.45 Mbps/W for the No-RN/SME-I/SME-O/MLP-I/MLP-O scenarios, respectively, which lead to a ~200-500% EE improvement. Similar conclusions can be drawn for SE as well, as depicted in Fig. 5-13, leading to a ~145-505% SE improvement.

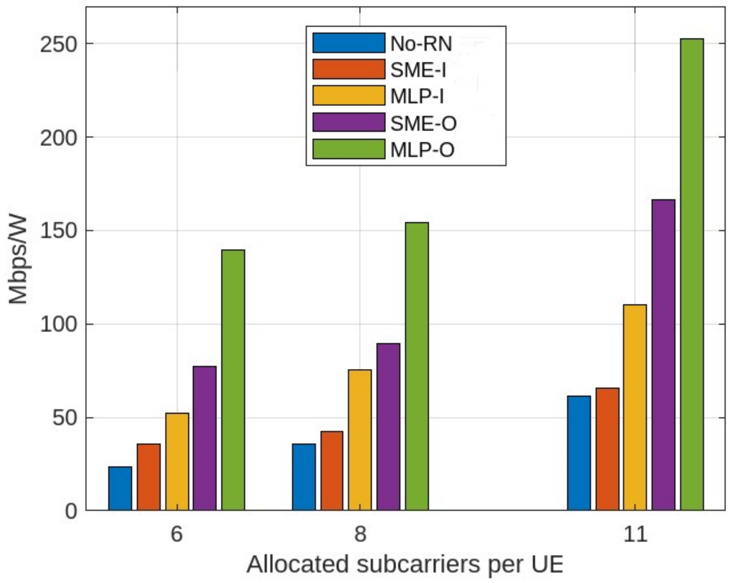


Figure 0-12: Mean total EE for various RN implementations (with DQL RN

It can be witnessed, also, from Figs. 5-10, 5-11 that the use of the DQL RN selection scheme further improves networks' KPIs, such as EE and SE, compared to the case where only the DL RN placement algorithm is enabled. In fact, comparing ML/DL Inband scenario (SME-I) in these two occasions (only DL-based RN placement or DL-based RN placement and DQL RN selection), a ~75% improvement in both EE and SE is depicted for 6 subcarriers per UE. For 11 subcarriers per UE the improvement is ~80%. Similarly, comparing ML/DL Inband scenario (SME-I) in these two occasions, a ~79% improvement in both EE and SE is depicted for 6 subcarriers per UE. For 11 subcarriers per UE the improvement is about ~83%. Thus, it is visible that DQL-based RN selection can further improve overall system's performance.

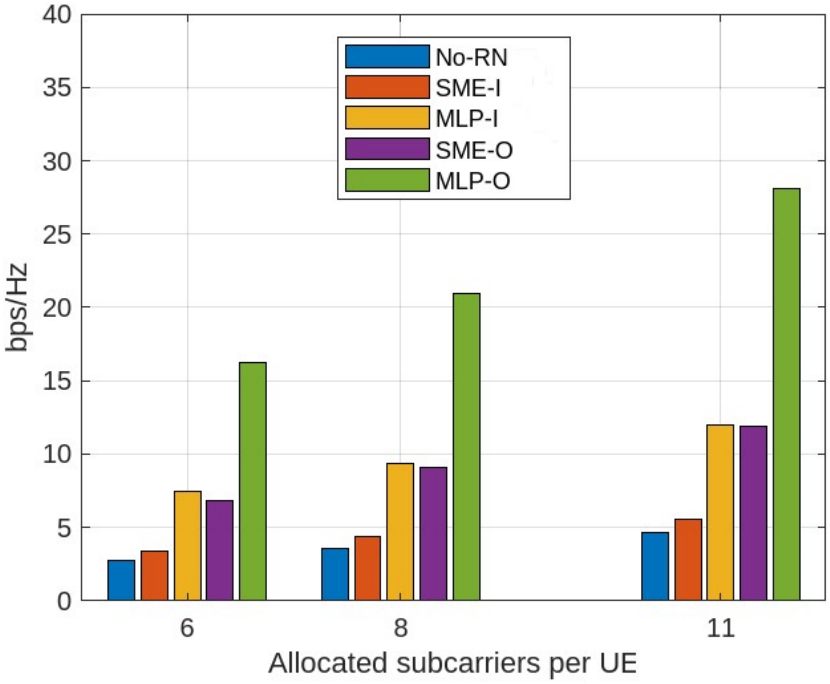


Figure 0-13: Mean total SE for various RN implementations (with DQL RN

5.6 Outcomes – Discussion

From the above presented analysis and, also, from Figs. 5-10, 5-11, 5-12, 5-13 the following outcomes can be witnessed:

- The proposed joint RN placement and selection DL/DRL-based framework can improve the performance of 5G/B5G networks, by the improvement of key network metrics, such as EE and SE.
- Concerning comparison with other state-of-the-art approaches the proposed models are evaluated in a two-level basis. More specifically:
    - The first level concerns the comparison of the proposed DL-enabled RN placement models with a 5G/B5G system where RNs are statically deployed and non-ML optimization techniques are utilized. From the subsection A it is visible that both EE and SE levels are improved by ~30% compared to such a system (as described in [CONF-1]).
    - The second level concerns the comparison of the joint RN placement and selection framework with a 5G/B5G system where RNs are statically deployed and non-ML optimization techniques are utilized. It is derived by the analysis in subsection B that the DRL-based RN selection algorithm contributes even more on the EE and SE improvement. In fact, these KPIs can be improved by up to ~80% compared to [CONF-1].
    - Moreover, our DL/DRL approach overperforms other state-of-the-art approaches that are not utilizing ML/DL models for RN placement and/or

selection. For example, the proposed scheme in [194] reaches up to ~50% improvement in EE levels compared to a state-of-the-art-approach. Moreover, our approach has similar or better performance compared to recently proposed ML-based schemes. For example, the proposed scheme in [195] reaches about ~80% EE improvement compared to a non-ML state-of-the-art approach.

- Finally, it should be mentioned at this point that, in general, Outband RN orientations overperform Inband ones in all scenarios under test. However, in Outband cases, extra bandwidth has been pre-allocated to RNs. Thus, despite the aforementioned gain over Inband ones, in real-world scenarios Outband RNs have extremely high deployment costs, due to the external resources and necessary hardware needed.

Finally, a key aspect when designing AI/ML algorithms is the computational complexity gain that is achieved compared to traditional optimization (non-ML) approaches. In the aforementioned performance evaluation this is achieved in the following ways:

- As it is presented in Tables 5-4, 5-5 both DL models need~4 to 5 minutes for the training phase. After this phase, the response to select the best performing RNs deployment is instant. In this analysis we should add the time for dataset generation which is ~2 hours. In the approach presented in [CONF-1], ~1 hour is needed for a round of ~100 MC simulations.
- Finally, in the same context, as far as the DRL RN placement scheme is considered, each one of the C cells needs some time (~1 to 2 minutes as the NNs there are lightweight) for the models' training, while dataset generation is performed online and, thus, there is no need for extra time there. As is is visible, the aforementioned computation time is extremely lower than the one of a full MC simulation.

Chapter 6: Conclusions and Future Work

In this chapter, the main takeaways of this doctoral thesis are discussed, while, also, its key contributions are summarized (Paragraph 6.1). Additionally, some indicative further research directions stemming from this are briefly present (Paragraph 6.2).

6.1 Conclusions and key contributions of the PhD thesis

5G networks deployment delivered fundamental and disruptive changes in the architecture, infrastructure, and operational attributes of the wireless networks. 5G networks have been deployed to deal with the massive connectivity and the diversifying user requirements, which formed a highly competitive and volatile communication environment. As the research works and the relevant 3GPP standardization reports are reaching towards B5G and 6G networks, the aforementioned user requirements are becoming even stricter, making the process of designing wireless networks able to provide a seamless user experience with superior QoS and QoE, even more demanding. Moreover, new application areas, such as IoT, AR/VR, holographic communications, are rising in the dawn of B5G networks, raising the need for new communication standards and newcoming physical layer techniques to serve massive data traffic levels and congestion.

In this environment, the significance of efficient RRM policies definition is of massive significance. The limited radio resources should be allocated in an intelligent manner to serve an increasing number of simultaneously interconnected devices, located in dense network orientations. Another vital aspect in designing effective RRM policies in 5G/B5G networks is the effective utilization of all the available spectrum, and the reduction of overall system's power consumption. In this framework, the network metrics of EE and SE are identified as the major ones to maximize, compared to previous networks generations where only capacity of throughput were considered.

To address all the above factors, in this doctoral thesis ML -and especially DL- has been deeply studied and utilized in order to solve several RRM-related problems, towards the construction of an end-to-end data-aided RRM decision support system in 5G/B5G networks. In fact the research efforts on the field of ML-based RRM have been tremendously increased, and will continue to do so as B5G/6G networks are deployed, as the need for intelligent support systems to perform real-time RRM decision making is visible. The ML utilization in the aforementioned problems intends to maximize the user satisfaction and provide the required QoS and QoE levels. In that sense, resource allocation in 5G/B5G networks becomes a dynamic data-aided and environment-driven mechanism to support increased network density, near-random mobility patterns, low-latency responses and massive connectivity, even in a decentralized manner. In parallel, motivated by the need to transition into energy-efficient and sustainable communications, this work focused on developing ML algorithms that guarantee EE and SE maximization, which leads to reducing unnecessary over-utilization of resources, hence accomplishing the optimal transfer of information with respect to both data exchange and the corresponding transmission power requirements.

The structure of the thesis, as also depicted in Preface, with regards to the identified problems and their respective solutions is summarized below:

Chapter 1 presents a brief overview of the 5G/B5G cellular networks, focusing on the 5G/B5G/6G user and performance requirements by a physical layer perspective. Moreover, the physical layer technologies that are of primary interest in 5G/B5G orientations, and, are, also, used in the proposed ML-based RRM algorithms throughout this thesis, are analysed.

Chapter 2 presents the ML techniques principles, which are the bases upon which our ML/DL models are constructed. In this framework, this chapter focuses on the theoretical background of advanced ML techniques, such as DQL or FL, which are of significant interest in the wireless communications domain, due to their ability to deal with complex problems and either provided environment-aider or distributed solutions.

Chapter 3 formulated the RRM problem in 5G/B5G orientations and, also, presents the research state-of-the-art, which is the thesis motivation, regarding the ML utilization in 5G/B5G networks RRM. Moreover, a comparative analysis is performed in order for the best-performing ML algorithms or types to be highlighted for each RRM sub-problem. Thus, guidelines, research directions and, also, open questions, that our algorithms try to answer, are identified regarding ML-based RRM in 5G/B5G networks. The findings of this chapter have been published in [J-1].

Chapter 4 considers the problem of KPI prediction in 5G/B5G networks. The significance of this problem for the efficient and effective RRM policies definition in 5G/B5G networks is analysed. Afterwards, several ML/DL techniques are compared regarding their performance in the throughput prediction problem in 5G/B5G orientations. The findings of this chapter have, also, been published in [J-1].

Chapter 5 focuses on the utilization of RN in the context of 5G/B5G networks. In fact, relaying-assisted communications is of increasing interest in wireless systems, due to their ability to increase network coverage and system's capacity without the need for RAN components stack to be deployed. Thus, RNs are a cost-efficient way to increase network's capabilities. RNs can support the new-coming 5G/B5G application scenarios such as sensor networks, IoT devices communication, AR/VR, but can, also, be vital in personalized (private) 5G deployments (e.g. 5G defense networks). Thus, the problem of the optimal placement and selection of RNs inside each cell's coverage area has gained research interest.

As far as the RN placement problem is concerned, this thesis proposes two DL-based techniques, deployed either in a CL or FL manner. Moreover, these algorithms are tested either knowing the relevant CSI parameters or not (which is really common in real-world scenarios). The performance evaluation of the aforementioned algorithms regarding ML KPIs, indicated that the proposed approaches overperform state-of-the-art ones.

As far as the RN placement problem is concerned, a novel environment-aided DQL framework is proposed, which is based on the joint user EE and SE maximization. However, an intelligent data-aided framework in attached to the aforementioned DWL solution, so that, also, the EE and SE of the overall system is maximized. Performance evaluation indicated that the joint RN placement and selection end-to-end ML scheme can maximized the achieved levels of EE and SE compared both to a non-ML-aided system, but, also, with other literature approaches. The findings of this Chapter have been published in [J-2] and [B-1]

Based on the previous overview, via this thesis a series of novelties and breakthrough approaches have been introduced, aiming at leading to a rethinking of how resource allocation can enhance network performance and lead to optimal outcomes of utilization, sustainability, and superior user satisfaction. A brief summary of the contributions of this work are presented as follows:

- First, an up-to-date state-of-the-art summary concerning ML-based RRM approaches is presented. In this context, the interest is mainly focused on the categorization of the ML-based RMM schemes proposed in the literature, in terms of the type of learning, and, thus, on defining the optimal ML solution in various RRM sub-problems (KPIs prediction, user, subcarrier and power allocation, etc.), with respect to different network metrics (i.e., QoS, quality of experience (QoE), throughput, etc.). In order to achieve this, the general RRM problem is formulated, while significant non-ML approaches and their limitations highlighted, as well. Then, the state-of-the-art concerning ML-based approaches in 5G/B5G RRM is presented. As already mentioned, these approaches are categorized by the type of ML models used by each one of them (Supervised, Unsupervised, Reinforcement). Furthermore, the coexistence of MEC and distributed learning techniques is analyzed, as it can tackle various challenges, especially concerning the training time of ML models.
- Through the above procedure, representative conclusions are drawn, as far as which ML models are appropriate in each RRM related sub-problem, based on the

network orientation. Moreover, limitations in current research efforts, open issues and discussion over the state-of-the art approaches are highlighted in an effort to both present potential solutions in these considerations and motivate future work on these fields. Thus, guidelines and research frameworks are proposed regarding AI/ML utilization for efficient resource allocation in 5G/B5G networks.

- In order to highlight the significance of AI/ML implementation in RRM, the problem of throughput prediction is investigated, as an indicative RRM task, treated either as a classification or a regression problem. Various ML algorithms are considered, results are presented, and performance is evaluated, based on selected ML KPIs for each task.
- Through the above-described analysis, limitations and open issues concerning AI/ML utilization in 5G/B5G networks are witnessed and potential solutions are described.
- The problem of RN placement to maximize the number of active users in each cell of the cellular topology is formulated. Thus, given only the number of the RNs per cell to be deployed and a set of potential geographical positions (x-y coordinates of potential RNs), the *k* best-performing RNs are selected to serve the active users in each cell. The aforementioned selection is performed subject to three main constraints. The first one is the minimization of pathloss for each accepted user, the second refers to the minimization of the total transmitted power by each deployed RN, while the latter is the maximization of the total accepted users in the topology. Moreover, the proposed algorithm is tested in two different simulation scenarios. The first one considers the presence of ideal CSI, while the latter considers no CSI at all.
- To tackle the aforementioned problem, we propose two efficient offline RN placement ML/DL algorithms which focus on fast response times taking into consideration the constraints previously presented. The fist DL algorithm considers an ANN orientation, while the latter considers a LSTM one.
- After the optimal placement of the RNs in each cell’s coverage area, we formulate the problem of optimal RN selection for each accepted user in the topology. In other words, for users not served directly by the BSs, either for pathloss or power consumption reasons, the optimal RN (from the k eligible) should be selected to serve them.
- To solve the aforementioned problem, we propose an energy efficient RL-based algorithm to select the optimal beam (RN) to serve each accepted user in the topology. A DQL/RL algorithm is utilized for this scope. In this context, EE and SE are the KPIs that determine algorithm’s transitions.
- Finally, all presented approaches are evaluated by extensive system level simulations in different usage scenarios. Performance evaluation indicates that the joint DL-based RN placement and selection scheme can overperform state-of-the-art approaches in improving various network KPIs, such as EE and SE.
- To sum up, the utilization of DL/DRL schemes, both for efficient RN placement in each cell of the cellular topology and for RN selection, which forms a full ML/DL-assisted RRM framework focusing on both EE and SE, is the key novelty of this thesis.
- Finally, concerning distributed ML approaches, a review of the most recent FL-based approaches in PHY is performed focusing on different sub-problems (RRM, channel estimation, beamforming, etc.). Afterwards, the FL schemes' advantages over state-of-the-art CL schemes are, also, discussed. Finally, challenges in the

design and implementation of such approaches are identified, and, thus, relevant future research directions are given.

- Moreover, an indicative comparative simulation scenario is performed to display the potential gains of FL methods implementation in PHY. More specifically, we develop, train and test several ML models for RN placement in 6G networks. The ML models are deployed either in a CL or an FL manner. Thus, performance evaluation discusses the FL advantages and disadvantages compared to existing (CL) solutions. In this way, relevant conclusions are made.

6.2 Future Work

The work summarized in this thesis proposes a meaningful and general ML-based framework, where the intelligent decision-making processes leveraging resource allocation policies for enhancing EE, fairness, and provision of superior QoS and QoE delivery in 5G/B5G. Fellow researchers can derive interesting extensions stemming from this work in RRM-related topics both in CL and FL network designs, where users' characteristics play a key role in system's optimization, applicable in many aspects of the upcoming deployment and research for B5G, and especially 6G, networks.

Some interesting directions for further research are identified as a continuation of this work. The list provided below is by no means exhaustive, as ongoing technology advancements and changing user requirements provide interesting opportunities to apply the proposed ML approaches in other fields of wireless networking.

New Spectrum - Terahertz (THz) communications: In 6G systems, where killer applications will be AR/VR and holographic communications, the need for large data transmission, results in a need for a very high-frequency band to support the increasing service scenarios demands [12]. THz and sub-THz bands have been proposed as a potential solution towards this direction. These bands are spread from 0.1 to 10 THz. However, several challenges have been witnessed in these scenarios. First of all, such a high-band transmission can serve really short-range coverage. Thus, ultra-massive MIMO antenna systems in BSs should be used and BSs should be located near to each other. Limitations can, also, be witnessed concerning hardware availability, transmission power, and increased pathloss [12].

Beyond MIMO communications: Ultra-massive MIMO communications, where antenna arrays can contain over 10,000 very small antenna elements, forming ultra-narrow band beams, and CF mMIMO, Access Points (APs) are spread in the coverage area to support UEs that demand service are of primary interest concerning RRM for B5G and 6G networks. These approaches can lead to significant mitigation in interference levels, while system's capacity can be increased a lot. However, ML-based RRM tasks are becoming extremely difficult in such orientations due to the significant data amount (large datasets) needed for ML models training.

Beyond Relay Communications: RISs, as presented, also, in Chapter 1 are proposed as an efficient solution to enhance connectivity in 6G networks, taking into account the hardware and deployment costs. RISs have a relay role in end-to-end communication, and, as a sequence, they can efficiently be used in blind network spots or to extend the coverage area of the network. RIS placement and selection problems can be also (similarly to RNs) solved effectively via ML/DK techniques.

Distributed ML and FL: Some key aspects that will be of interest in the future regarding distributed ML and FL are the following:

- Scalability and user characteristics: Some of the key usage scenarios of 6G networks is the holographic, AR/VR and UxV communications. In these scenarios, user density and mobility are of vital interest. The research works performed until now, assume either static UEs or established CSI conditions. Thus, an escalation of the current approaches towards more complex evaluation scenarios will be significant for the feasibility of the proposed FL solutions.
- Privacy and security: As addressed in the previous subparagraph, FL by definition provides a level of security in the inter-communication between the different edge devices and the centralized entity. However, as addressed by [188], traditional encryption and/or authentication solutions could be of interest. On the same framework, modern-era physical layer security algorithms could, also, be of interest, in order to handle massive connectivity IoT or vehicular network scenarios.
- Interoperability with other enabling technologies: 6G networks are expected to both use and leverage current 5G technologies, but also utilize new-coming ones to support the extended requirements presented in paragraph I. In this framework, the deployment of FL schemes in cooperation with satellite communications [44], quantum communication [196] or even blockchain [197] technologies.

Physical Layer Security: Physical layer security plays a crucial role in ensuring the confidentiality and integrity of wireless communication in B5G. It involves exploiting the characteristics of the physical channel to enhance the security of wireless transmissions. As already presented, RRM in B5G networks is responsible for efficient allocation and utilization of radio resources to meet the diverse requirements of different services. The integration of physical layer security techniques into RRM algorithms can significantly enhance the overall security and performance of B5G networks. By considering the security requirements during resource allocation and scheduling decisions, RRM can mitigate eavesdropping and jamming attacks, optimize transmit power allocation, and allocate suitable modulation and coding schemes [198]. This integration of physical layer security and RRM in B5G networks ensures secure and reliable communication, paving the way for the deployment of advanced applications and services [199].

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Appendix– Publications

Publications in international scientific journals

[J-1] **I. A. Bartsiokas**, P. K. Gkonis, D. I. Kaklamani and I. S. Venieris, "ML-Based Radio Resource Management in 5G and Beyond Networks: A Survey," in *IEEE Access*, vol. 10, pp. 83507-83528, 2022, doi: 10.1109/ACCESS.2022.3196657.

[J-2] **I. A. Bartsiokas**, P. K. Gkonis, D. I. Kaklamani and I. S. Venieris, "A DL-Enabled Relay Node Placement and Selection Framework in Multicellular Networks," in *IEEE Access*, vol. 11, pp. 65153-65169, 2023, doi: 10.1109/ACCESS.2023.3290482.

Publications in the proceedings of international scientific conferences

[CONF-1] K. A. Psilopanagiotis, **I. A. Bartsiokas**, P. K. Gkonis and D. I. Kaklamani, "On Relay-Based Subcarrier Allocation and Power Management in 5G Multicellular Networks," *2022 IEEE 95th Vehicular Technology Conference: (VTC2022-Spring)*, Helsinki, Finland, 2022, pp. 1-6, doi: 10.1109/VTC2022-Spring54318.2022.9861029.

Publications in book chapters

[B-1] **I. A. Bartsiokas**, P. K. Gkonis, A.K. Papazafeiropoulos, D. I. Kaklamani and I. S. Venieris, "Federated Learning for 6G HetNets' Physical Layer Optimization: Perspectives, Trends, and Challenges," Encyclopedia of Information Science and Technology, Sixth Edition, IGI Global, 2025, pp. 1-28, doi: 10.4018/978-1-6684-7366-5.ch070.

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[C-1] P. K. Gkonis, "A Survey on Machine Learning Techniques for Massive MIMO Configurations: Application Areas, Performance Limitations and Future Challenges," in *IEEE Access*, vol. 11, pp. 67-88, 2023, doi: 10.1109/ACCESS.2022.3232855.

[C-2] H. M. F. Noman et al., "Machine Learning Empowered Emerging Wireless Networks in 6G: Recent Advancements, Challenges and Future Trends," *IEEE Access*, vol. 11, pp. 83017-83051, 2023, doi: 10.1109/ACCESS.2023.3302250.

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